On the Flow-Performance Relations among Delegated Institutional Portfolios

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Abstract

Institutional funds – delegated institutional portfolios catering to pensions and nonprofit organizations – have unique features and distinctive flow-performance relations. Fund investors face high search costs as institutional funds have low disclosure requirements and limited ability to advertise. Further, there is no liquidity sharing among investors of separately managed accounts. We find that while overall institutional fund flows are sensitive to past performance, funds with high investor search costs have extra flow sensitivity to good past performance, and funds offering a low degree of liquidity sharing exhibit muted flow sensitivity to poor past performance. Finally, institutional fund flows are negatively correlated with subsequent fund performance at short, intermediate, and long horizons. These findings suggest that in the institutional fund market, search costs and liquidity are important factors for investment delegation decisions, and that frictions in this market may have undermined the effectiveness of the delegation decisions.

1 Introduction

Institutional investors known as "plan sponsors" – e.g., pensions and nonprofit organizations such as foundations and endowments – are big players in the financial market. Their investments in publicly-traded securities are nowadays predominantly in the form of delegated portfolios managed by external investment advisors (referred to as "institutional funds" subsequently). In terms of the total assets under management, these institutional funds dwarf the hedge funds, and until recently, exceeded the retail mutual funds.[1]

This study examines the investment delegation decisions of plan sponsors by looking at the relations of institutional fund flows with both past and future fund performance. There is already a large literature on the flow-performance relations among mutual funds. However, the institutional fund market has several important features that set it apart from the retail mutual fund market, and there is much to learn about the economic implications of these features. For example, it is well-observed that plan sponsors are capable of making informed decisions, but they may suffer from agency problems when plan managers – e.g., treasurers for corporate pensions – have their own career interests in mind (Lakonishok, Shleifer, and Vishny, 1992). Consistent with such agency problems, Lakonishok, et al. (1992) and subsequent studies find that institutional funds on average underperform benchmarks.[2] Further, Del Guercio and Tkac (2002) report that when choosing funds, plan managers mitigate their career risk by relying on tangible metrics that can be defended ex post.

Our work follows the footsteps of these pioneering studies; however, we focus on two features of this market whose effects have yet to be clearly understood. First, despite the huge amount of assets and the sophisticated clientele, the institutional fund market has

[1] The relative size of the institutional fund sector vs. the mutual fund sector varies over time. According to Del Guercio and Tkac (2002), in 2000, the total tax-exempt assets managed by top 1000 institutional fund management firms are \$7.2 trillion, exceeding the total mutual fund assets of \$5.3 trillion. According to Blake et al. (2013), in 2009, the total assets of U.S. pension funds are \$9.7 trillion, trailing the \$11.1 trillion assets managed by mutual funds. This relative size change is in part due to the shift of retirement savings from defined benefit plans (which invest through institutional funds) toward defined contribution plans (which invest through retail mutual funds).

[2] Other empirical studies with similar conclusions include Coggin, Fabozzi, and Rahman (1993) and Christopherson, Ferson, and Glassman (1998), etc.. Using more recent data, Busse, Goyal, and Wahal (2010) report average underperformance and somewhat mixed evidence on performance persistence.

relatively low information transparency. This has to do with the regulatory landscape of the fund market. Except for institutional mutual funds, delegated institutional portfolios are exempt from the Investment Company Act (1940), and thus (among other things) face low disclosure requirements. Also, the exemption-status prevents them from advertising or engaging in other marketing activities that may be construed as general solicitations. As a consequence, plan sponsors have limited information available when they search for fund managers. This situation is in contrast to the mutual fund market, where retail investors are "bombarded with advertising and columnists offering advice, as well as direct solicitations by salespeople" (Sirri and Tufano, 1998). Furthermore, fiduciary duties require plan sponsors to search through a sufficiently large number of funds and learn sufficient details about the chosen fund. Their search process is costly in terms of time and efforts.[3] How significantly the search costs affect plan sponsors' investment delegation decisions is an issue we attempt to understand empirically.

The second feature of interest is liquidity sharing, or the lack of it, in the institutional fund market. Liquidity sharing is the crucial mechanism used by mutual funds to provide liquidity to fund investors even when fund investments are illiquid. Mutual funds pool investments from a large number of investors; on a daily basis, redemptions and purchases by investors of a fund partially offset. When a mutual fund has to sell securities to meet investors' net redemptions, the associated trading costs are shared by all fund investors. By contrast, a typical institutional fund has only a small number of investors, each with a large amount of investments, making liquidity-sharing ineffective. In fact, many institutional portfolio products are in the form of separately managed accounts. Trading costs for a separate account are born by the owner of that account alone, and are not shared with any other investors of the same fund. The popularity of separate accounts can be understood from the basic economics of this market; that is, plan sponsors have long investment horizons and thus for most of the time they are not concerned with liquidity or liquidity sharing. However,

[3]Plan sponsors often hire investment consultants in their fund selection process. Investment consultants collect information about fund performance and manager characteristics and assist plan sponsors in the fund screening and selection. Their presence may alleviate search costs, but may also create another layer of agency problems in this market.

when they do need liquidity – for example, when exiting a poorly performing fund – lack of liquidity sharing may significantly affect their decisions.

We examine a large sample of 3,311 actively-managed domestic institutional equity funds during the period from 2001 to 2011. In our first look at how institutional fund flows respond to past performance, a general pattern from the data is that institutional clients flee away from poorly-performing funds as much as they chase top-performing funds, while being relatively insensitive to the middle range of performance. The symmetric flow response pattern confirms the early finding by Del Guercio and Tkac (2002), and is in an interesting contrast to the lack of mutual fund flow sensitivity to poor performance (e.g., Sirri and Tufano, 1998).

It is also worth noting that the symmetry in flow response is consistently observed across a wide range of performance measures, from simple returns, fund alphas, returns in excess of benchmarks and peers, to information ratio, Sharpe ratio, and Treynor ratio. The fact that institutional fund flows are sensitive to multiple risk-adjusted performance ratios is consistent with the different roles active funds may play in an investor's entire portfolio. In addition, flows are much more sensitive to long-term (three-year) performance than to short-term (one-year) performance. These results suggest that relative to retail mutual fund investors, institutions monitor fund performance more diligently, rely more on risk-adjusted measures to evaluate performance, and have longer investment horizons. They are also consistent with the notion that plan managers mitigate their career risks by responding to tangible and justifiable performance metrics.

We then investigate how search costs affect flow response to fund performance. The typical fund search process involves two steps. Plan sponsors first rely on certain concrete criteria (e.g., performance record and manager tenure) to screen through a large number of funds and narrow down the list. Then they perform detailed research about the small number of candidate funds, often involving in-person interviews with the fund managers. Intuitively, when investors face high costs to learn about funds, at the screening stage they would rely heavily on fund past performance, and set a high bar on performance in order to quickly narrow down the list for further costly investigation. As a consequence, funds with good past performance have an extra high chance of getting investors' attention, while funds falling outside the top performance ranks could be easily ignored. Huang, Wei, and Yan (2007) provide a model to describe this effect and report supporting empirical evidence from mutual funds.

To examine this effect, we consider several institutional fund characteristics that are associated with low search costs, such as funds from large family complexes, funds offered by mutual fund firms, and funds attracting a high proportion of foreign clients. We find that institutional funds with lower investor search costs have significantly lower flow sensitivity to top range of fund performance, and significantly higher flow sensitivity to the middle range of fund performance. For example, based on the piecewise linear regression approach of Sirri and Tufano (1998), we show that for funds from the largest families (top tercile in terms of number of funds offered), the flow sensitivity to good fund performance is 60% lower, while the flow sensitivity to the middle range of performance is 26% higher, relative to other funds. These results suggest a strong effect of search costs on the flow-performance relations.

The lack of liquidity sharing also bears a significant mark on the flow response pattern. Liquidity sharing likely matters most when plan sponsors exit poorly performing funds. Consistent with this hypothesis, we find that flow sensitivity to poor performance is significantly muted when investors to a fund predominantly hold their assets in separate accounts. Further, given the lack of liquidity sharing, we expect the heterogeneity in investors' liquidity need matters for the flow sensitivity. Consistent with this hypothesis, we find that flows of funds with a higher proportion of small accounts (which likely have low concern for liquidity) are significantly more sensitive to poor performance.

Due to liquidity sharing, a fund can offer liquidity to its investors even when fund investments are illiquid. Thus, we expect the effect of liquidity sharing to be different from that of fund investment liquidity. Indeed, we find that the flow response patterns for funds with more illiquid investments are quite different from those for funds with low liquidity sharing. Additionally, in joint regressions, the effect of liquidity sharing and the effect of investment liquidity both remain significant and do not drive away each other. Such findings also cast an interesting contrast with the illiquidity externality effect Chen, Goldstein, and Jiang (2010) have observed in the mutual fund market; that is, in the presence of liquidity sharing among investors, mutual fund flows are extra sensitive to poor performance of illiquid funds (in a way similar to "bank-runs"). Due to lack of liquidity sharing, institutional fund flows do not exhibit such illiquidity externality.

Finally, we examine the relation of institutional fund flows with future fund performance. Berk and Green (2004) predict that fund flows chase past performance but do not predict future performance when investors rationally learn about manager ability from past performance. One would expect such a prediction to work better in the institutional fund market than the mutual fund market as plan sponsors are more likely to be rational learners. However, we find that institutional fund flows are negatively correlated with future performance at short (3 months), intermediate (12 months), and long (12 to 24 months) horizons. For funds experiencing large outflows, there is significant performance improvement at short, intermediate, to long horizons; for funds experiencing large inflows, subsequent performance significantly deteriorates at the long horizon. Further, the negative relation between flows and future performance cannot be fully explained by disciplinary role of fund outflows, or the performance-chasing behavior of inflows, or the diseconomy of scale at the fund level.

This finding again offers an interesting contrast with observations in the mutual fund market. Mutual fund flows have a positive relation with short-term future performance (i.e., "smart-money") and a negative relation with long-run future performance (i.e., "dumb money").[4] By comparison, there is no "smart-money" in the institutional fund market, and only a pervasive "dumb-money" effect. After we rule out apparent explanations such as mere performance chasing and decreasing return to scale, what exactly drives this phenomenon remains an open question. Both Del Guercio and Tkac (2002) and Goyal and Wahal (2008) point out that many non-performance factors unobservable to researchers may drive institutional fund flows and the hiring and firing of institutional fund managers. Possibly, such

[4]See, e.g., Gruber (1996), Zheng (1999), Wermers (2003), Sapp and Tiwari (2004), Keswani and Stolin (2008), Friesen and Sapp (2007), and Frazzini and Lamont (2008).

non-performance factors have attracted institutions to certain funds, which turn out to disappoint them in terms of future performance.[5]

Our paper is related to the early work of Del Guercio and Tkac (2002), who document symmetric response by institutional fund flows to good and poor past performance, as well as flow patterns consistent with the agency problems. However, their study faces a few data constraints, such as a relatively small sample with survivorship bias, and flow observations only at the annual frequency. The much expanded industry size, improved data quality, and availability of data on various fund characteristics enable us to pursue a systematic update of their key analysis. Also related are two studies on the flow-performance patterns of institutional mutual funds, a relatively small subsample of institutional funds. Evans and Fahlenbrach (2012) confirm the symmetric response of institutional mutual funds to good and poor performance, and find that retail mutual funds with institutional twins (i.e., institutional portfolios with same investment strategies) have better performance. James and Karceski (2006), on the other hand, find that institutional mutual funds with retail mates actually perform worse than those without.[6] The most important difference between our work and these existing studies is our focus on the effects of search costs and liquidity sharing.

Related to the relation of fund flows with future institutional fund performance, several studies have examined fund manager switching by plan sponsors, with somewhat contrasting findings. Blake, Rossi, Timmermann, Tonks, and Wermers (2013) report that U.K. plan sponsors are able to make successful delegation decisions when they switch from institutional fund managers with broad mandates to those with narrow mandates, and from single manager to multiple managers. By contrast, Goyal and Wahal (2008) find that subsequent

[5]Possibly, both plan sponsors' delegation decisions and stock mispricing are driven by common investor sentiment in the market. This is similar to the conjecture offered by Frazzini and Lamont (2008) to explain the "dumb money" observation for mutual funds. Also possibly, the reliance on a common group of investment consultants may have caused herd-like, ineffective, delegation decisions by plan sponsors (Jenkins, Jones, and Martinez, 2014).

[6]Sialms, Stark, and Zhang (2015) report that flows from defined contribution pension plans are symmetrically sensitive to past fund performance, mainly due to fund switchings by plan sponsors; however, their fund switchings do not predict future fund performance. Defined contribution plans invest in retail mutual funds, not the institutional funds.

performance is indistinguishable between fund managers fired and hired by U.S. plan sponsors. Compared with Goyal and Wahal's (2008) finding (on the consequence of a single plan sponsor's delegation decision), the significant negative relation of fund flows with future performance documented in our study highlights the interesting effect of collective delegation decisions by multiple plan sponsors.

Finally, Jenkinson, Jones, and Martinez (2014) find that investment consultants' recommendations have significant influence on institutional fund flows, and that consultants' recommendations tend to be negatively correlated with future fund performance. Their results suggest a potential role of investment consultants in explaining the negative relation documented by this paper between fund flows and future performance.

The rest of the paper is organized as follows. Section 2 describes the data and the measures of fund flows and fund performance. Section 3 presents the empirical results. Section 4 concludes.

2 Data and Empirical Methodology

2.1 Data

The Investment Company Act of 1940 requires mutual funds to price their shares and disclose performance to fund investors on a daily basis. By contrast, there is no such reporting requirement for institutional funds in general. In fact, the disclosure practice of institutional funds (other than institutional mutual funds) is quite similar to that of hedge funds. In order to attract investments, institutional funds voluntarily provide periodical performance data to investment consultants and certain commercial data vendors. This has been the main sources of data on this industry.

A few existing studies on the institutional fund industry use data from investment consultants. For example, Lakonishok et al. (1992) use the data provided by the consultant SEI. Data used by both Coggin et al. (1993) and Christopherson et al. (1998) are from Frank Russell. Ferson and Khang (2002) use data from Callan Associates. Goyal and Wahal (2008) use data from Mercer. And the U.K data used by Blake et al. (2013) are from the consultant subsidiary of BNY Mellon. As pointed out by Lakonishok et al. (1992), investment consultants often only have data on funds that their clients invest in or may potentially invest in, and thus may be subject to potential selection biases. The data collected by consultants in early periods are typically not survivorship bias free.

A few commercial vendors have attempted to gather more complete coverage of this industry, and have made their data available to consultants, plan sponsors, investment managers, as well as researchers. The early data vendors include Plan Sponsors Network (PSN) and the Mobius Group; both later acquired by Informa Investment Solutiuons (IIS) (in 1998 and 2006 respectively). Currently, IIS and eVestment Alliance are the two main commercial data vendors on institutional fund data. Del Guercio and Tkac (2002) use data from Mobius, Busse et al. (2010) use data from IIS, and Jenkinson et al. (2014) use the eVestment data, respectively. There are similar quality issues on data collected by these vendors during early periods. However, data quality has improved over time. For example, Del Guercio and Tkac (2002) note that the Mobius data they use are subject to the survivorship bias. By contrast, Busse et al. (2010) note that the data from IIS (the successor to Mobius) are free from the survivorship bias.

Based on our conversations with data vendors, the differences between the IIS data and the eVestment data are mainly in terms of their coverage for early years and for international advisory firms. IIS has better fund coverage for early periods, while eVestment has better coverage for institutional fund managers outside the U.S.. In terms of U.S. domestic institutional funds, since the 2000s, the coverage by eVestment is comparable to that of IIS and both are free of the survivorship bias. In addition, the eVestment data have more information on the management firm characteristics and fund characteristics, which are important to our study.

For the above considerations, we choose eVestment as our main data source. The information provided by eVestment include quarterly assets under management, monthly (as well as quarterly and annual) returns, fee scheme, investment approach, the profile of investment advisory firms, as well as information about the investment accounts that reveal the characteristics of investment clients. The sample in our study is the actively-managed institutional funds that are domiciled in U.S. and mainly invest in domestic equities, for the period from 2001 to 2011. Even though data for earlier years are available, we focus on this relatively recent period to alleviate data quality issues discussed above.

The eVestment data deal with the survivorship issue in the following way. If a fund stops reporting to the database at a certain time point, the fund is classified as "inactive". The database provides the date on which a fund becomes inactive, and keeps all the historical data prior to the inactive date. Note that survivorship is not the only known issue for self-reported performance data. To alleviate the incubation bias (e.g., Evans 2010), we only include fund performance observations after a portfolio's inception date and exclude funds with assets under management below $25 million (as funds in incubation typically are small). To address the back-filling bias, we require at least 24 months of prior performance data for a fund to be included in analysis.

We proceed to discuss a few unique reporting conventions in the institutional fund industry to help understand the way we process the data. Although collectively referred to as "institutional funds" in our study, delegated investment portfolios catering to plan sponsors actually take several forms, ranging from separately managed accounts, commingled funds, to the institutional version of mutual funds. For this reason, the institutional funds are termed "products" in the database. Each product consists of a number of investor accounts. As noted by Del Guercio and Tkac (2002) and Busse et al. (2010), because separate-account clients can request various portfolio restrictions or adjustments, accounts under the same product can have slightly different portfolio compositions even though they are managed by the same manager using the same strategy. This creates complications in performance reporting.

The fund returns reported in the database are "composite returns". They are returns net of trading costs but gross of management fees, on "composite portfolios", i.e., combined holdings from various representative investment accounts of the same product. Similar to the practice in the mutual fund industry, fees charged on an institutional account are typically a flat percentage of the account size, and performance-related incentive fees are rare. The percentage fees typically decline when the account size exceeds certain breakpoints, e.g., $10 million, $50 million, and $100 million. Therefore, the after-fee returns of individual accounts under the same product can be different due to both difference in portfolio compositions and difference in fees.

For all the results reported in the paper, we measure after-expense fund return as the reported composite return minus the maximum percentage fee (i.e., the fee rate on the smallest possible account). The return calculated this way represents the experience of an investor with a small account. We have alternatively calculated returns based on the minimum percentage fee or the percentage fee corresponding to the average account size. We have also performed analysis by only including return records where the composite portfolio represents a very high fraction of the entire portfolio (following Del Guercio and Tkac 2002). The analyses based on such alternative fee assumptions and composition restrictions do not result in any significant departure from our conclusions. For brevity we do not tabulate the results of such alternative analysis in the paper.

Fund flow calculation follows Sirri and Tufano (1998). Each quarter we define the percentage flow for fund i in quarter t as:

$$\text{Flow}_{it} = \frac{\text{AUM}_{it} - \text{AUM}_{it-1}(1 + R_{it})}{\text{AUM}_{it-1}}, \tag{1}$$

where AUM_{it} is the assets under management by fund/product i at end of quarter t. R_{it} is the after-expense net return for fund i in quarter t. To alleviate the impact of outliers, we winsorize the flow measures at the 1st and 99th percentiles cross-sectionally in each quarter before using them in analysis. Note that the flow calculation is affected by the percentage fee assumption. However, the percentage fee variation in the data is much smaller than the variation of quarterly fund assets changes. Based on back-of-envelop calculations we conclude that the influence of fee assumption on the flow-performance relation is negligible.

2.2 Summary Statistics on the Institutional Fund Sample

Our sample includes actively-managed US domestic equity funds from eVestment data, for the period from 2001 to 2011, with data filters on fund size and length of prior performance data. The eVestment dataset has a total of 4,487 unique actively managed US equity funds during our sample period. Among them, 3,860 unique funds have AUM above $25m for at least one quarter. After we further impose the requirement of at least 24-month prior performance data, the final sample size comes to 3,311 unique funds. These funds are managed by 896 unique investment firms. The AUM filter and the performance data filter each have a substantial impact on sample size; however they are necessary for guarding against various biases associated with the self-reported data.

Panel A of Table 1 reports sample statistics for the investment advisory firms in the eVestment data that manage sample institutional funds, in each year from 2001 to 2011. The number of firms starts at 245 in 2001, peaks at 654 in 2007, and ends at 609 in 2011. The average number of institutional domestic equity funds they manage (including index funds and not restricted to the sample funds) is relatively stable across years, at around 4 per firm. The average US domestic equity assets under management is above $10b per firm in 2001, due to the existence of a few very large firms in the early sample period. The average AUM quickly drops to $6.9b in 2002 as new firms are included the sample. The average AUM peaks in 2006 and 2007, at above $11b, and then drops dramatically to $6b in 2008 at the advent of the financial crisis. It recovers afterwards, and is back at above $10b by 2011. Some of these advisory firms also manage mutual funds. We match the firm names with those in the CRSP Mutual Fund database to identify the mutual fund assets they manage. The number of institutional investment firms that also manage mutual funds fluctuates between 50 and 113 during the sample period.

Panel B of Table 1 reports the number of sample funds and the means and medians of fund assets and fund flows by year. The number of sample institutional funds is 673 in 2001, jumps to 1,025 in 2002, peaks at 2,173 in 2006, and ends at 2,247 by 2011. Part of the increase is due to the actual growth of the industry, while another factor is the expanded fund coverage over time by eVestment, especially at the beginning of our sample period.[7] The average AUM fluctuates between $1,186m and $2,332m during the sample period. The median AUMs are much smaller relative to mean AUMs, suggesting the presence of a small number of very large funds in the sample. The lowest mean and median of AUM are found in the year 2008, due to large losses incurred by funds and large withdrawals by fund investors during the financial crisis. The mean and median quarterly fund returns are mostly positive, except for the year of 2002 and 2008. The mean quarterly flows fluctuate around zero, with more frequent negative observations during the later half of the sample period.

Using the IIS data, Busse, Goyal, and Wahal (2010) report 4,617 unique institutional funds during the period of 1991-2008. Their sample size is comparable to ours (4,487, as mentioned earlier) before imposing the AUM filter and the performance data filter. In their Table 1, the number of funds is above 2,500 in each year from 2001 to 2008, while the average AUM is much smaller than that reported in our Table 1. For example, in 2006 (the year with peak AUMs in both papers), the average AUM in their sample is $1,470m while that in our sample is $2,332m. Thus, the sample difference is mainly due to the fact that we have excluded funds with very low AUMs.[8]

The eVestment dataset has information about a rich set of fund characteristics. In Panel C of Table 1, we provide distributional statistics on several fund characteristics used in later analysis. The characteristics include quarterly flows, total number of accounts in a fund, percentage quarterly change in number of accounts, average account size, fund age, percentage fees, fund idiosyncratic return volatility (i.e., standard deviation of monthly residual returns based on the Carhart four-factor model using rolling 36 months of data), the proportion of AUM from foreign clients, the proportion of assets held in separate accounts, and

[7] The exclusion of first 24 months of performance data along results in a reduction of 447 unique funds (from 1120 to 673) for the year of 2001. Among such funds, about half have inception dates in 2000 or 2001; the rest have inception dates prior to 2000 but their first performance numbers in the eVestment data are during 2000-2001. The impact of this requirement on sample size for subsequent years is much smaller. We obtain similar results when loosening the restriction on the prior performance data.

[8] Jenkinson et al. (2014) also use the eVestment data. They do not impose any restrictions on AUM or prior performance data. However, they include only a subsample of funds in a few specific marketcap and value/growth categories. For this reason, their sample size is smaller than ours (except during 2001 and 2002).

the percentages of accounts with assets below \$10m ("small accounts"). We compute the pooled distribution of these characteristics over all available fund-quarter observations in the sample. The distributional statistics include the number of observations, mean, median, the first and third quartiles, and the standard deviation.

Many of these characteristics set the institutional fund market apart from the mutual fund market. One characteristic to note is that the median number of accounts in a fund is only 15, indicating that unlike retail mutual funds, a typical institutional fund has a small number of investors. However, the mean and standard deviation of the number of accounts are both quite large, due to the existence of some institutional mutual funds with a large number of investors. The mean and median of average account size are quite large, at \$138m and \$40m, respectively, while the large standard deviation suggests substantial heterogeneity in average account sizes. Despite that flows are already winsorized at the 1% and 99%, the standard deviation of quarterly flows is quite large, at 23.94%, while the interquartile spread (i.e., the difference between the third and the first quartile) is only 7.63%. The existence of extreme flows in the data is consistent with the notion that due to a small number of accounts, adding one account or the withdrawal of an existing account can easily cause large flows. Average fund age is between 13 and 14 years, more than that of typical active equity mutual funds. The average percentage fees (maximum level of fees per year charged on small accounts below \$1m) is 0.87% per year, lower than the typical 1% for active equity mutual funds. Also note that the standard deviation of fees, at 0.3%, is much smaller than the standard deviation of quarterly flows reported in the same table, or the standard deviations of quarterly returns reported in Panel B of the table.

The table shows that separate accounts are prevalent. At the mean and median, they account for 68% and 92% of fund AUM. Assets from foreign investors on average account for 6.72% of AUM, but the large standard deviation indicates that some funds have a very large fraction of foreign client assets. Finally, on average 45% of the accounts have assets below \$10m, which are considered small relative to the average account size. Note that two of these fund characteristics – assets from foreign clients and the percentages of small accounts –are less frequently reported in the data. Their observations are only about one third of other fund characteristics, and concentrate toward the later part of the sample period.

2.3 Performance Measures

We employ several performance measures in the analysis. The first two performance measures are those commonly used in the studies on mutual funds – the average monthly after-expense fund return and the monthly Carhart (1997) four-factor alpha of the after-expense returns. The factor data are obtained from Wharton Research Data Services (WRDS).

In addition, we consider the following two groups of performance measures. First, a common practice in the institutional fund market is that plan sponsors award narrowly-defined investment mandates to fund managers (Bank for International Settlements, 2003; Blake et al, 2013). For equity portfolios, the mandates typically restrict funds to specific investment styles. The rationale of such a practice is perhaps still open to interpretation (e.g., Blake et al, 2013; van Binsgerben, Brandt and Koijen, 2008; He and Xiong, 2013). Nonetheless, it is quite possible that plan sponsors pay attention to these styles when evaluating fund performance, and thus making institutional fund flows sensitive to the style-specific benchmarks popular in the industry.

Accordingly, we construct two style related performance measures. The benchmark-adjusted return is a fund's average return in excess of the average return of the self-claimed benchmark index (as provided by eVestment). The peer-adjusted return is a fund's average return in excess of the average returns of all active institutional equity funds with the same investment style. The eVestment data have 26 US domestic equity benchmarks self-claimed by active funds in the sample. We group these benchmarks into 12 styles along the size and value dimensions. The Appendix provides the details for the mapping of equity benchmarks into investment styles. We assign each fund into a style based on its self-claimed benchmark.

Second, although fund alpha is the typical measure of the stock selection ability of an active fund manager, plan sponsors may rely on other quantities when deciding how much of their investments should be allocated to an active fund. Approximately, the roles of active funds in plan sponsors' entire portfolios fall into the following three categories. First, some plan sponsors many select one active fund, or a small number of active funds to represent their entire equity holdings. Second, it is increasingly popular among plan sponsors to combine a few active funds with passively managed index funds to achieve the optimal risk-return trade-off. Third, it has been known that some large plan sponsors, such as California Public Employees' Retirement System (CalPERS), use a fund-of-fund approach. That is, they pool a large number of actively managed funds into a well-diversified portfolio. These different roles of active portfolios are discussed in standard investment textbooks; for example, Bodie, Kane, and Marcus (2013).

Depending on the role an active fund plays in the entire portfolio, there are different measures appropriate for investment allocation decisions (hence their relevance to fund flows). Assume that a plan sponsor's objective is to maximize the Sharpe ratio of the entire portfolio. In the first scenario, since only one active fund or a few such funds serve as the entire risky portfolio, the appropriate performance measure for selecting funds is the Sharpe ratio. In the second scenario, where a small number of active portfolios are to be combined with passive funds, the appropriate performance measure is the information ratio, as proposed by Black and Treynor (1973). Finally, for the fund-of-fund approach, Treynor (1965) proposes a name-sake Treynor ratio as performance measure.

Accordingly, we include information ratio, Sharpe ratio, and Treynor ratio as additional performance measures. Information ratio is the four-factor fund alpha divided by the standard deviation of residuals from the same factor model. Sharpe ratio is the average fund return in excess of the average riskfree rate (proxied by the 1-month US Treasury yield), divided by the standard deviation of fund returns. The Treynor ratio is the average fund return in excess of the average riskfree rate, divided by the market beta of the fund. Data on factors and the riskfree rate are from WRDS.

3 Empirical Results

This section consists of the following parts. Section 3.1 documents the general patterns in flow response to past fund performance. Section 3.2 examines the effect of investor search costs. Section 3.3 focuses on the effect of liquidity sharing. Section 3.4 contrasts the liquidity sharing effect with the effect of illiquid fund investments, as well as that of search costs. Finally, Section 3.5 looks at the relation between fund flows and future performance.

3.1 Flow Response to Past Performance: General Patterns

3.1.1 Symmetry in Flow Response to Good and Poor Performance

Figure 1 plots the basic relation between institutional fund flows and past performance. We pick two basic performance measures to illustrate the pattern – the rolling 12-month after-expense fund net return (Panel A) and the rolling 36-month after-expense Carhart (1997) four-factor alpha (Panel B). Each quarter we rank funds based on their past performance into deciles and plot the time-series average of flows of each fund decile in the figure.

Similar to retail mutual fund investors, plan sponsors are sensitive to good fund performance. In Panel A, when the performance rank increases from the ninth to the tenth (top) decile, flow increases approximately from 4% to 6%. Importantly, plan sponsors are also responsive to poor performance. As the performance rank drops from the bottom second to the bottom decile, flow drops approximately from -2% to -4%. The pattern holds when past performance is measured by the four-factor alpha. By comparison, existing studies report that the flow-performance relation among mutual funds is essential flat for poor performance (e.g., Sirri and Tufano, 1998). Thus, plan sponsors are more sensitive to poor fund performance than retail investors. Also note that the flow-performance relation in the middle performance deciles is slightly flat, a pattern more visible from the multivariate regression analysis described below.

Using the various performance measures introduced in the previous section, we conduct multivariate regression analysis to examine the institutional flow-performance relation and control for other factors affecting flows.

We follow the piecewise linear regression specification that is common in studying mutual fund flows (e.g., Siri and Tufano, 1998). Each quarter, we assign a fractional rank (denoted as *Rank*) ranging from zero to one to each fund, based on the fund's past performance relative to the cross-section of funds. We then define three piecewise-linear performance variables: Lowperf = min(*Rank*, 0.2) for funds in the bottom performance quintile, Midperf = min(0.6, *Rank* - Lowperf) for funds in the middle three quintiles, and Highperf = min(0.2, *Rank* - Lowperf - Midperf) for funds in the top quintile. Each quarter, we run the following cross-sectional regression:

$$\text{Flow}_{it} = a + b_1\text{Lowperf}_{it-1} + b_2\text{Midperf}_{it-1} + b_3\text{Highperf}_{it-1} + \text{CONTROLs} \tag{2}$$

where CONTROLs represents a set of control variables, including the idiosyncratic volatility of fund return based on the Carhart (1997) four-factor model, the log of the previous quarter fund assets (AUM), the percentage fee, and the log of fund age. We report the time-series average of the estimated coefficients and the time-series t-statistics. In Panels A and B of Table 2, fund performance is measured over past 12 months and over past 36 months (with a minimum 24 months of returns required), respectively. And correspondingly, the standard deviation of idiosyncratic fund returns is estimated over either the 12-month or the 36-month horizon.

There are a few observations to note. First, consistent with known patterns for retail mutual funds, plan sponsors are sensitive to good performance. For all model specifications and over both performance horizons, the coefficient for Highperf is significantly positive. For example, in the case where performance is measured by past 12-month average return, the coefficient for Highperf is 0.24, suggesting that a one-percentile increase in the performance rank leads to 0.24% additional quarterly inflows across funds in the top performance quintile. Across various performance measures over the 12-month horizon (Panel A), the magnitude of this coefficient is consistently in the range of 0.175 to 0.243, and the t-statistic for the coefficient is always above 6.0. Across various performance measures over the 36-month horizon (Panel B), the coefficient for Highperf is consistently in the range of 0.176 to 0.304, with a t-statistic always above 6.0. Second, flows are sensitive in poor performance as well. When performance is measured by the past 12-month average return, the coefficient for Lowperf is 0.217, also statistically significant at the 1% level. The difference between the coefficients on Highperf and Lowperf, 0.023, is statistically insignificant. The results are consistent under various alternative performance measures. The coefficients on Lowperf are always significantly positive. The differences in the coefficients between Highperf and Lowperf are always insignificant, suggesting quite symmetric flow response to poor and good performance. Third, the coefficient for Midperf also tends to be significantly positive; however, the magnitude of this coefficient is much lower relative to those for Lowperf and Highperf. This suggests that fund flows are relatively less sensitive to the middle range of performance. Finally, we note that institutional fund flows have significantly negative relations with fund assets, age, and idiosyncratic return volatility, and the relation with fee tends to be insignificant (with one exception, when the performance measure is the 36-month Treynor ratio).

Overall the regression results confirm the patterns in Figure 1. Plan sponsors withdraw money from poorly performing funds as much as they chase funds with good performance. It is noteworthy that these findings are similar to those reported by Del Guercio and Tkac (2002), despite that we are looking at a more recent period (2001-2011 vs. 1987-1994) with a significantly larger sample of funds (3,311 vs. 562). Also similar to their findings, the adjusted R-squares of the flow-performance regressions are relatively low, suggesting that non-performance factors may be important in driving plan sponsors' portfolio delegation decisions.

3.1.2 Flow Response to Multiple Performance Measures

There are substantial correlations among these various performance measures (confirmed in untabulated analysis). Thus a natural and economically meaningful question is whether flows are more sensitive to certain performance measures over others. We investigate this issue here.

In Panel A of Table 3, we examine whether fund flows are more sensitive to the performance over the past one year or over the past three years. For this purpose we include the piecewise linear functions of both one-year and three-year performance measures in the same regression. We also include the standard deviation of residual fund returns over both the one-year and three-year horizons as control variables. The results suggest that flows are more sensitive to the longer-term performance. For example, using fund alpha as the performance measure, the coefficients for Lowperf, Midperf, and Highperf based on past one-year performance are 0.115, 0.003, and 0.080, respectively. By contrast, the corresponding coefficients based on past three-year performance are much higher, at 0.221, 0.090, and 0.258 respectively. The t-statistics for the coefficients on the three-year performance measures are also much higher. The pattern is similar across alternative performance measures. Also interestingly, while the coefficients on the one-year performance volatility and three-year performance volatility are both significantly negative, the magnitude of the coefficient and the t-statistics on the three-year volatility is much larger. Thus, plan sponsors appear to pay more attention to long-term performance than to short-term performance.

In Panel B of Table 3, we run a horse-race among the four "return-based" performance measures – average return, alpha, benchmark-adjusted return and peer-adjusted return, using piecewise linear functions of each. We focus on the three-year performance measures here. The regression results show that the coefficient on Midperf based on average return loses statistical significance, while the coefficients on Highperf based on benchmark-adjusted return and peer-adjusted return turn negative. The only performance measure that remains significantly positive for all three piecewise linear functions is fund alpha.

In Panel C of Table 3, we include the piecewise linear functions of all three performance ratios – information ratio, Sharpe ratio, and Treynor ratio – as explanatory variables. The piecewise linear functions of the Treynor ratio either lose statistical significance or turn negative. By contrast, those of the information ratio and Sharpe ratio remain significantly positive, and the coefficients for those based on the information ratio tend to have the highest t-statistics. Based on these observations, we infer that plan sponsors either rely on one or a small number of active funds to represent their entire risky equity portfolio, or combine active funds with passive funds to construct optimal risky equity portfolio. However the fund-of-fund approach, which is consistent with the use of Treynor ratio for performance evaluation, is relatively rare among plan sponsors.[9]

3.1.3 Changes in Number of Accounts

Another interesting feature of institutional funds, relative to retail mutual funds, is in the frequency of extreme fund flows. As shown in Table 1, institutional funds typically have only a few numbers of accounts, each with a large amount. When a plan sponsor changes its portfolio allocation, it often results in a large change in the assets of the fund. In other words, extreme fund flows are often the result of changes in the number of institutional accounts.

Here, we take a direct look at the source of extreme flows – the changes in number of accounts. In Table 4, we report regression results based on the percentage change of number of accounts, i.e., the change in the number of accounts during a quarter divided by the number of accounts at the beginning of the quarter as the dependent variable. The explanatory variables are the same as those in (2). We also look at the same set of performance measures, and focus on the three-year fund performance.

The results show that the percentage changes in number of accounts are sensitive to both good and poor past performance, while less sensitive to the middle range of performance. Note that under the Sharpe ratio, the coefficient on Lowperf is even significantly higher than the coefficient on Highperf.

[9]We do not run a horse race between the "return-based" measures and the "ratio-based" measures because of the multi-collinearity concern. For example, consider the information ratio, which is a combination of fund alpha and standard deviation of residual returns. In addition, we find that the cross-sectional variations in the information ratio, Sharpe ratio, and Treynor ratio are mainly driven by the numerators of these ratios, which are alpha and excess return. The cross-sectional variations in their denominators, i.e., idiosyncratic volatility, return volatility, and beta, are much smaller.

3.2 The Effect of Search Costs

Next, we investigate the effect of investor search costs. In part due to their exemption status from the Investment Company Act of 1940, institutional funds (other than those organized as mutual funds) have low disclosure requirements and are not permitted to engage in any marketing activities that can be construed as general solicitations. Thus, when plan sponsors begin the fund search process, unless they have already invested in a fund, their knowledge about the fund tends to be very limited. Further, possibly related to their fiduciary duties, plan sponsors conduct detailed investigation about a candidate fund before making an investment with the fund. Given the nature of available information, plan sponsors' fund search process typically involves two steps. First, they rely on several tangible criteria (such as past performance, tracking error, manager tenure, etc.) to screen through a large number of funds and narrow down to a small number of candidate funds. Second, they perform detailed investigation to collect tangible and intangible information about the candidate funds before choosing one. The investigations often involve in-person interviews with fund managers.

The search process and the high search costs involved make the institutional funds fitting well into the model developed by Huang, Wei, and Yan (2007). They show that due to the existence of a fixed component of search cost ("participation cost" in their paper), investors are only willing to learn about a new fund when its past performance is sufficiently good. Thus, search costs increase flow sensitivity to the top range of performance, while a reduction of such participation costs will reduce the flow sensitivity to top performance but may increase the flow sensitivity to the middle range of performance. We test this implication empirically.

Huang et al. (2007) develop three empirical measures as proxy for low investor search costs for mutual funds – affiliation with large fund families, high expense ratio, and affiliation with fund families that have star funds. These measures are based on the idea that funds from large families and star families have high ex ante "visibility" to investors and that high expense ratios are likely associated with high marketing and distribution efforts by funds, thus lowering investor search costs. Following their study, we use affiliation with large families and star families as proxies for low investor search costs. However, we do not consider institutional fund fees a valid proxy, because institutional funds do not engage in substantial marketing, and thus the association between fee and investor search cost is not expected to be strong.[10] In addition, we consider two measures unique to the institutional fund market. One is fund affiliation with a mutual fund management firm, based on the idea that mutual fund firms tend to be ex ante more visible due to their ability to advertise. Another is fund reach to foreign investment clients, based on the idea that the ability of a fund to attract foreign investors is an indication that the fund enjoys an effective distribution channel or high visibility.

Specifically, the four variables are constructed as follows. First, the indicator variable Large Family is for funds managed by advisory firms ranked in the top tercile in terms of the number of U.S. domestic equity funds managed (including index funds and not restricted by prior performance data or fund AUM). Second, the indicator variable Mutual Fund Firm is for institutional funds managed by mutual fund advisory firms. To identify mutual fund advisory firms, we match the firm names in the eVestment data with those in the CRSP mutual fund data, and ensure positive mutual fund assets managed by the firms at the time of fund ranking. Third, the indicator variable Foreign Clients is for funds ranked in the top tercile in terms of the fraction of AUM from foreign clients. As noted in Table 1, the data for the foreign client AUMs are spotty. To ensure sufficient data coverage, we take the time series average in the fraction of foreign client AUM for a given fund over the quarters the data are available, and then obtain a one-shot cross-sectional (but time-invariant) ranking of this variable. Finally, we measure the fraction of funds from an advisory firm that are ranked in the top quintile in terms of past 36-month four-factor alphas. The indicator variable Star Firm is for funds managed by firms ranked in the top tercile in terms of the fraction of their top-performing funds. Except for Foreign Clients, we use quarterly fund ranking to come up with the other three proxies.

As a warm-up, we first perform Fama-Macth regressions of fund flows onto fund past

[10] The spill-over effect of "visibility" from star funds to other funds in the same family may also depends on marketing and advertising. Thus this effect may be weak for institutional funds as well.

performance, each of the above four indicator variables for low search costs, and their interaction terms. The control variables are the same as those in Table 2. Because the analysis in Section 3.1 indicates that the fund flows most reliably respond to past 36-month four-factor alpha, we continue to use this performance measure variable (the cross-sectional alpha rank, to be exact) in subsequent regressions. The results are reported in Panel A of Table 5. The fund alpha rank spots significantly positive coefficients. Among the four search cost proxies, Large Family and Foreign Clients have significantly positive coefficients, suggesting that funds from larger families and funds capable of attracting more foreign investments have higher flows. The coefficient on the interaction term between fund alpha rank and search cost proxy is significantly negative for Large Family, and significantly positive for Star Family, suggesting that funds from larger families have lower flow-performance sensitivity while funds from star families enjoy enhanced flow sensitivity to past performance.

To pin-point the effect of search costs, however, we need to look at flow response to different segments of fund performance. In Panel B of Table 5 we use the three piecewise linear functions of the 36-month four-factor alphas as fund performance measures, and interact them with each of the four search cost proxies. As the results show, for the first three low search cost indicators, Large Family, Mutual Fund Firm, and Foreign Clients, their interaction terms with Highperf have significantly negative coefficients, and their interaction terms with Midperf have significantly positive coefficients. This suggests that funds with lower investor search costs have less sensitive flow response to high performance and more sensitive flow response to the middle range of performance, consistent with the hypothesized effect of search costs. The magnitude of the search cost effect is quite large. For example, using Large Family as the low search cost proxy, the coefficients on Midperf and Highperf are 0.077 and 0.366 respectively. The coefficients on their interaction terms with Large Family are 0.020 and -0.203 respectively. Thus, affiliation with large fund families reduces the flow sensitivity to high performance by 60% and increases flow sensitivity to middle range of performance by 26%.

However, the fourth indicator, Star Firm, has insignificant interaction terms with Highperf and Midperf. As discussed earlier, perhaps the spillover effect on fund visibility from star funds depends on effective marketing, and institutional funds generally do not engage in heavily marketing.[11]

3.3 The Effect of Liquidity Sharing

We now turn to the effect of (lack of) liquidity sharing. Institutional funds have three main product forms: separately managed accounts, commingled funds, and institutional mutual funds. In terms of assets in these product forms, separately managed accounts are by far the most popular, followed by mutual funds, and commingled funds the least. In separately managed accounts, each plan sponsor holds investments in its own account, not mingled with assets of other investors of the same fund. When an investor withdraws from an account, it bears the transaction costs on its own. In mutual funds, assets from a large number of investors are pooled together. Fund investors own shares of the fund, not directly the assets the fund invests in. Fund investors are guaranteed to purchase and redeem fund shares at the net asset value (NAV). Thus, the transaction costs associated with liquidating investments to meet net investor redemption needs are born by all fund investors. Commingled funds are partnerships of investors, where assets from a modest number of investors are pooled together, but often with restrictions on contributions or withdrawals. In sum, there is no liquidity sharing among separate account investors, full liquidity sharing among mutual fund investors, and somewhat limited liquidity sharing among investors of commingled funds.

In addition to the regulatory reason (i.e., exemption from Investment Company Act), the popularity of separate accounts is likely related to the low need for liquidity by plan sponsors on normal occasions. Plan sponsors typically have long investment horizons and do not expect frequent shuffling of their investments. When long-term investors pool their assets with short-term investors in the same mutual funds, they essentially provide liquidity services to short-term investors, without receiving any compensation and at the additional

[11]In the absence of marketing, the spillover effect in visibility from star funds could still exist if plan sponsors rely on star funds from the same advisory firm as one of the screening criteria. We are not aware of such practice, though.

cost of sharing the fund trading costs. Thus, plan sponsors with relatively large amount of investments tend to favor separate accounts.

However, when separate account investors do need liquidity, they have to bear all the trading costs of liquidating investments in the accounts. This may be a significant concern especially because the separate accounts tend to be large in size. Such occasions arise naturally when plan sponsors decide to shift investments out of poorly performing funds. Frequently, in order to reduce trading costs, plan sponsors hire dedicated "portfolio transition" managers to liquidate separate accounts. The popularity of portfolio transition service is an indication of the importance of trading costs, or lack of liquidity sharing, on plan sponsors' portfolio delegation decisions.

Given the above discussions, we examine two specific hypotheses related to the lack of risk sharing. The first is that when investor assets are predominantly in separate accounts, fund flows should have muted response to poor performance. The second is that given lack of risk sharing among the accounts, fund flows should be more sensitive to poor performance if a fund is dominated by small accounts; and on the other hand, when the average account size is large, fund flow response to poor performance may be muted.

Our proxy for lack of liquidity sharing, Separate Accounts, is an indicator for funds ranked in the top tercile in terms of the fraction of assets held in separate accounts. In addition, Average Account Size is an indicator for funds ranked in the top tercile in terms of the average size of an account. And Small Accounts is an indicator for funds ranked in the top tercile in terms of the proportion of small accounts (i.e., assets below $10m) in total accounts. As noted in Table 1, the observations for small accounts are spotty. To avoid losing too many observations, we first calculate the time series average of the proportion of small accounts for a given fund using all available quarterly data for such observations, and then perform one-time cross-sectional ranking. To construct the other two variables, Separate Account and Average Account Size, we rank funds quarterly. Collectively, we refer to these three variables as liquidity sharing proxies.

In Table 6 we perform Fama-MacBeth regressions to investigate the effect of lack of liquidity sharing. The regression specifications are similar to those in Table 5, except that low search cost proxies in Table 5 are replaced by liquidity sharing proxies. In Panel A of Table 6, the fund performance measure is the fund alpha rank. Note that the interaction term of Average Account Size with the fund alpha rank has a significantly negative coefficient, suggesting that large accounts tend to have muted response to fund performance. However, the interaction terms of Separate Accounts and Small Accounts with fund alpha rank have insignificant coefficients.

Panel B of Table 6 produces sharper test results for the hypotheses we are interested in. In this panel, fund performance is measured by the three piecewise linear function of fund alpha, Lowperf, Midperf, and Highperf. The coefficient for the interaction term of Lowperf with Separate Accounts is significantly negative, consistent with the notion that lack of liquidity sharing produces muted flow response to poor performance. The interaction term of Lowperf with Average Account Size, however, is insignificant. We conjecture that perhaps the heterogeneity in account size matters more than the average account size, in detecting the liquidity sharing effect. This is confirmed by the results involving Small Accounts. The interaction term between Lowperf and Small Accounts has a significantly positive coefficient, suggesting that small account holders are less constrained by lack of liquidity sharing, and thus are more responsive to poor performance. In addition, note that the coefficient for the interaction term between Midperf and Average Account Size is significantly negative, suggesting that large account holders tend to be more constrained in their response to the middle range of performance.

3.4 The Joint Effects: Illiquid Investments, Liquidity Sharing, and Search Costs

As we point out earlier, liquidity sharing is different from the liquidity of fund investments. A mutual fund could invest in illiquid securities and yet still offer liquidity service to its investors. In other words, liquidity sharing is the wedge between fund investments' liquidity and fund investors' liquidity. To highlight such a difference, in this section we investigate the effect of fund investment illiquidity on the flow-performance relations and contrast the results with the effect of liquidity sharing.

We construct three proxies for fund investment illiquidity. The first, Smallcap Funds, is an indicator for funds investing in smallcap and microcap stocks, based on the fund investment styles provided by eVestment. The second, Illiquidity Beta, is an indicator for funds ranked in the top tercile in terms of the beta of fund returns with respect to the illiquidity factor of Pastor and Stambaugh (2003). The beta is estimated quarterly, using rolling 36 months of data. The third, Pricing Frequency, is for funds priced at frequency lower than daily. Mutual funds are required to provide daily pricing in order to facilitate daily liquidity to fund investors. Many institutional funds also offer daily pricing. However, some institutional funds price fund values at monthly or even quarterly, possibly due to lack of liquidity in fund investments. Such low pricing frequencies prevent fund investors from withdrawing investments on short notices.

The regression results reported in Table 7 highlight the difference between the effect of illiquid fund investments and that of lack of liquidity sharing. For example, in Panel B of the table, the coefficients for the interaction terms of Lowperf with the two proxies, Smallcap Funds and Illiquidity Beta, are insignificant. By contrast, their interaction terms with Midperf are significantly negative while those with Highperf are significantly positive. The negative coefficients for the interaction with Midperf suggest that flow response to the middle range of performance is muted for illiquid funds.[12] Interestingly, the coefficient for the interaction term between Lowperf and Pricing Frequency is significantly negative, suggesting that low pricing frequency discourages investors from quickly fleeing away from poorly performing funds.

In Table 8, we perform regressions to investigate the joint effects of liquidity sharing and illiquid fund investments, by including proxies for both effects, and their interaction terms with the piecewise linear functions of fund alpha, as explanatory variables. We find

[12] A plausible explanation for the significantly positive coefficient for the interaction terms involving Highperf is the search cost effect – that is, investors face higher search costs for smallcap funds (due to low ex ante visibility of such funds).

that the patterns observed in the separate regressions of Table 6 and 7 largely retain in the joint regressions. For example, in the joint regressions, the coefficients for the interaction terms of Lowperf with Separate Accounts are always significantly negative, and those with Small Accounts are always positive. Further, the coefficients of interaction terms between Midperf/Highperf and Smallcap Funds/Illiquidity Beta are always significant. The interactions of Midperf with Average Account Size are always significantly negative, so are the interactions of Lowperf with Pricing Frequency.

In Table 9, we further include the search cost effect into the joint regressions. Due to the large number of combinations (4x3x3) among the proxies for search cost, liquidity sharing, and investment illiquidity, we do not report the results of all such combinations. Instead, we construct a combined measure for each effect. Specifically, to construct a combined measure for low search cost, we first convert fund tercile ranks based on the number of funds offered by the family into the values of 0, 0.5, and 1, and similarly convert the tercile rank of the fraction of foreign client assets. For mutual fund firm status we keep the value of o 0 and 1. We then take the average of these three variables to obtain the combined measure, termed SEARCH. We do not include the variable related to star firms because this effect is insignificant in Table 5. For the three characteristics related to liquidity sharing, we perform similar conversions, except that we do it inversely for the fraction of small accounts as its effect is the opposite of the other two. The resulting average score is termed SHARE. Finally, for fund characteristics related to investment illiquidity, we keep the values of 0 and 1 based on the smallcap fund status and low pricing frequencies, but convert the tercile ranks on illiquidity beta into the values of 0, 0.5, and 1, and then take the average of the three variables. The resulting measure is termed ILLIQ. Higher values of SEARCH and ILLIQ mean higher investor search costs and more illiquid fund investments respectively, while higher values of SHARE indicate less risk sharing.

The results show that the effects of search cost, lack of liquidity sharing, and fund investment illiquid all remain significant in the joint regressions. We observe significantly negative (positive) coefficient for Highperf*SEARCH (Midperf*SEARCH), significantly negative coefficient for Lowperf*SHARE, and significantly negative (positive) coefficient for Highperf*ILLIQ (Midperf*ILLIQ). Thus, these three effects are relatively distinctive from each other.

Finally, we note that in the institutional fund market, we do not observe the externality effect of illiquidity investments proposed by Chen, Goldstein, and Jiang (2010) for mutual funds. This effect is similar to bank runs – in the presence of liquidity sharing, when a fund has to liquidate illiquid investments to meet the redemption demand by some investors, the staying investors bear the liquidation costs. Thus, every investor wants to be the first to get out when an illiquid fund suffers from poor performance. This illiquidity externality generates extra flow sensitivity to poor performance.

In our analysis on institutional funds, we do not find evidence of such illiquidity externality. In particular, this effect would result in a significantly positive coefficient for the interaction term between Smallcap Funds (or Illiquidity Beta) with Lowperf. However, in Table 7 and 8, the relevant coefficients are always insignificant. This is perhaps easy to explain: according to the model of Chen et al. (2010), the effect of illiquidity externality critically depends on the existence of liquidity sharing among investors. Put it differently, the absence of the illiquidity externality effect in the institutional fund market is in fact consistent with the prediction of Chen et al. (2010).

3.5 Fund Flows and Future Performance

We now turn to the relation of institutional fund flows with future performance. Our analysis here builds upon the baseline hypothesis outlined by Berk and Green (2004). In their model, fund managers have differential skills and investors rationally learn about manager skills from past performance. The competitive supply of fund capital and the diseconomies of scale drive subsequent performance to the point where no further abnormal returns can be expected. In other words, flows chase past performance but do not predict future fund performance.

Given the perception that plan sponsors are sophisticated investors capable of rational learning, the institutional fund market is a fitting test ground for the prediction from the Berk and Green model that fund flows do not predict future performance. If flows turn out to predict fund performance in the data, then in the framework of their model, it could be the case that learning about fund skills is inefficient or investors' capital supply to funds is not fully competitive. Berk and Tonks (2007) offer an empirical observation consistent with this prediction even though it is off the equilibrium outcome of the model. They show that mutual funds underperforming for two years consecutively are more likely to continue to underperform and such funds also are the ones with less dramatic outflows. In contrast, funds only underperforming poorly in one year have significantly larger outflows and show no evidence of subsequent underperformance.

Other mutual fund studies also offer interesting observations for comparison. Several studies, such as Gruber (1996) and Zheng (1999), report a short-term smart-money effect; i.e., fund flows are positively correlated with subsequent fund performance at relatively short horizons. Sapp and Tiwari (2004) find that this "smart money" effect no longer holds after controlling for stock return momentum. Using data on fund holdings, Wermers (2003) find that both smart money and price momentum explain the observed positive correlation between fund flows and subsequent performance. By contrast, at relatively long horizons, the flow-performance relation is found to be negative. Friesen and Sapp (2007) show that incremental investments to funds inferred from fund flows earn negative returns. Frazzini and Lamont (2008) find that stocks heavily held by funds receiving large inflows subsequently underperform stocks heavily held by funds experiencing large outflows at horizons beyond one year. They point out that fund flows may be affected by investor sentiment, which generates a temporary impact of stock valuation that gets reversed in the long run. Such evidence is consistent with a "dumb-money" effect.

We examine whether there are similar smart-money and dumb-money phenomena in the institutional fund market using Fama-MacBeth regressions. The dependent variable of the regression is monthly abnormal fund returns from the Carhart (1997) four-factor model. Specifically, in each month, we estimate the coefficients of the four-factor model using rolling

36 months of data (with a minimum of 24 months of data required). The monthly abnormal return is the return of the month in excess of the fitted value from the regression. In one set of regressions, the main explanatory variable is the cross-sectional percentile rank of quarterly fund flow. In a second set of regressions, we separately measure the positive part and the negative part of the quarterly flows and include them jointly as regressors. Additional explanatory variables include the log fund AUM, the log fund age, the percentage fee, and fund idiosyncratic return volatility.

Fund abnormal returns are measured at three different horizons: 1 to 3 months, 1 to 12 months, and 13 to 24 months after measuring the quarterly fund flows and other explanatory variables. We refer to them as the short, intermediate, and long horizons. In these regressions, the abnormal fund return of a given month is used in 3 or 12 regressions involving flows during the past 3 to 24 months. To aggregate the regression coefficients, we follow the spirit of the Jegadeesh and Titman (1993) non-overlapping approach. Specifically, we first take the average coefficients of regressions involving the abnormal fund returns of the same month (i.e., the dependent variable), and then computing their time-series means over different months and the corresponding time series t-statistics. A similar approach has been adopted by Wermers, Yao, and Zhao (2012).

The results are reported in Panel A of Table 10. The basic pattern from the table is that fund flows are significantly negatively correlated with future abnormal fund returns at all three horizons. Therefore, a dumb-money effect appears to prevail in the institutional fund market. Unlike mutual fund flows, there is no short-horizon smart money for institutional fund flows.

The results reported in the same table also help us evaluate several conjectures about the cause(s) of this negative relation between fund flows and subsequent performance. In particular, we are interested in the following three hypotheses. One hypothesis is the monitoring or disciplinary effect of fund outflows. Specifically, plan sponsors withdraw money dramatically from underperforming managers, who subsequently exert efforts to turn around performance. Since this hypothesis suggests investor monitoring at work, "dumb-money" would be a mislabel. A second hypothesis focuses on excessive performance chasing by investors. That is, plan sponsors may have chased past fund performance too aggressively, causing temporary overvaluation of stocks held by winning funds and undervaluation of stocks held by underperforming funds. The third hypothesis is related to the diseconomy of scale – if funds with good past track record subsequently become too large due to large inflows, they may lose edge in delivering performance.

Under the first hypothesis, the negative relation between flow and subsequent performance should be mainly driven by fund outflows. We investigate this hypothesis by looking at the regression results involving the positive and negative parts of fund flows separately. The results are also reported in Panel A of Table 10. Indeed, negative flows bear significantly negative coefficients over the short, intermediate, and long horizons. However, positive flows have highly negative coefficients for at the long horizon (months 13-24). Therefore, the disciplinary role of fund outflows is not the whole story.

Under the second hypothesis, the relation between flows and future performance relation should be explained away by past fund performance. Indeed, past fund alpha has a positive coefficient, and significantly so at the long horizon. However, as we see in the table, after controlling for lagged fund alpha, the coefficients on flow rank and the positive and negative parts of flows remain significant. Therefore, the negative flow-performance relation is not purely due to the performance-chasing enthusiasm by plan sponsors.

Under the third hypothesis, the predictive flow-performance relation should be explained by a negative relation between fund size and performance. The diseconomy of scale effect is confirmed in the data, as the coefficients on log fund AUM are significantly negative. Yet again, the negative relation between fund flow and subsequent performance remains significant after controlling for fund size. Thus, diseconomies of scale cannot fully explain the dumb-money effect.

Fund age and fee are both negatively related to future performance, consistent with observations on mutual funds. In addition, idiosyncratic return volatility does not have a significant impact of subsequent performance. The significant coefficient on past fund alpha indicates performance persistence. This is in contrast to the weak performance persistence for institutional funds reported by Busse, Goyal, and Wahal (2010).[13]

In Panel B of Table 10, we change the dependent variable from percentage fund flows to the percentage changes in the number of accounts (which is a proxy for extreme flows), and repeat the regressions performed in Panel A. At the short horizon of three months, the coefficients for the account change rank and the negative percentage account change are negative but statistically insignificant. At the intermediate horizon of 12 months, the coefficient for the account change rank is insignificantly negative, while the coefficient for the negative percentage account change is significantly negative. At the long horizon of 12-24 months, the coefficients on both the account change rank and the positive percentage account change are significantly negative. Therefore, the pattern of negative relation with future performance by fund flows is largely retained by the percentage change in accounts, especially at longer horizons.

As an additional note, the significantly negative relation between fund flows and future performance we document is not necessarily in contradiction with Goyal and Wahal (2008). They find insignificant difference in the subsequence performance between fund managers fired and hired by plan sponsors. There is a key difference between the two studies –they look at the action of one plan sponsor alone, while the flows and the changes in the number of accounts in our analysis are the result of joint actions by multiple plan sponsors.

Overall, our findings indicate a robust negative relation between fund flows and subsequent fund performance. This relation is not completely driven by the disciplinary role of outflows, or over-enthusiastic performance-chasing by plan sponsors, or diseconomies of scale in the investment management industry. Del Guercio and Tkac (2002) and Goyal and Wahal (2008) point out that many non-performance factors unobservable by researchers may drive institutional fund flows and plan sponsors' manager hiring and firing decisions. We conjecture that such non-performance factors are potentially at work and some of these fac-

[13]Our untabulated analysis shows that the difference in the performance persistence evidence is mainly due to the difference in sample selection. Busse et al. (2010) include funds with assets below $25m while we do not. The small funds tend to have more extreme but less persistent performance.

tors turn out to undermine the effectiveness of plan sponsors' fund selection decisions. Two specific factors may account for the pattern. First, as conjectured by Frazzini and Lamont (2008) for mutual funds, both fund flows and stock misvaluation may be influenced by a common investor sentiment factor, which causes long-run return reversal. Second, many plan sponsors receive advices from a small group of investment consultants (Jenkinson et al. 2014). It is possible that the reliance on the common investment consultants may have caused plan sponsors to make herd-like delegation decisions that are ineffective.

4 Conclusions

This study provides a systematic examination of the flow-performance relations among institutional funds. We find that institutional fund flows are sensitive to various risk-adjusted measures of past fund performance, more sensitive to long-term performance than to short-term performance, and symmetrically sensitive to good and poor performance. This provides an interesting contrast with the flow response patterns in the mutual fund market. However, while institutional fund flows appear responsive to past fund performance, they do not signal plan sponsors' ability of picking winning funds. There is no smart money effect. If any, plan sponsors' money flocks to funds that deliver disappointing performance subsequently. Thus, our findings thus present a more complicated picture on the sophistication of institutional investors in making investment delegation decisions.

The institutional fund market has the characteristics of high investor search costs and lack of liquidity sharing. We find that these two features have significant impact on the flow-performance relations. Funds with high investor search costs have high flow sensitivity to top performance and reduced flow sensitivity to the middle range of performance. Funds with lower liquidity sharing exhibit more muted flow response to poor performance. Improving information transparency and liquidity sharing could potentially increase the welfare of participants in this market.

Appendix

We group all actively-managed US institutional equity portfolios into 12 styles based on their size and book-to-market characteristics of the self-claimed benchmarks for each fund. The mapping details are provided below.

	Investment style	Self-claimed benchmark
1	allcapcore	eA US All Cap Core Equity
1	allcapcore	eA US Enhanced All Cap Equity
2	allcapgrowth	eA US All Cap Growth Equity
3	allcapvalue	eA US All Cap Value Equity
4	largecapcore	eA US Enhanced Russell 1000 Equity
4	largecapcore	eA US Enhanced S&P 500 Equity
4	largecapcore	eA US Large Cap Core Equity
5	largecapgrowth	eA US Enhanced Russell 1000 Growth Equity
5	largecapgrowth	eA US Large Cap Growth Equity
6	largecapvalue	eA US Enhanced Russell 1000 Value Equity
6	largecapvalue	eA US Large Cap Value Equity
7	midcapcore	eA US Enhanced Mid Cap Equity
7	midcapcore	eA US Mid Cap Core Equity
8	midcapgrowth	eA US Mid Cap Growth Equity
9	midcapvalue	eA US Mid Cap Value Equity
10	smallcapcore	eA US Enhanced Small Cap Equity
10	smallcapcore	eA US Micro Cap Core Equity
10	smallcapcore	eA US Small Cap Core Equity
10	smallcapcore	eA US Small-Mid Cap Core Equity
11	smallcapgrowth	eA US Micro Cap Growth Equity
11	smallcapgrowth	eA US Small Cap Growth Equity
11	smallcapgrowth	eA US Small-Mid Cap Growth Equity
12	smallcapvalue	eA US Micro Cap Value Equity
12	smallcapvalue	eA US Small Cap Value Equity
12	smallcapvalue	eA US Small-Mid Cap Value Equity

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Table 1: Summary Statistics

This table reports the summary statistics for actively-managed institutional US domestic-equity funds and their investment advisory firms. We require funds to have a minimum AUM of $25m and to have at least 24 months of prior return data to be included in the sample. Panel A reports the summary statistics for the advisory firms managing at least one sample fund in a given year from 2001 to 2011. The statistics include the number of advisory firms, average number of U.S. institutional equity funds (not restricted to sample funds) per firm, and the average U.S equity asset under management by the firms, as well as the number of firms that also manage mutual funds. Panel B reports the number of institutional funds in the sample, the cross-sectional means and medians of assets under management (AUM), quarterly returns and quarterly flows during each sample year (2001-2011). The numbers of funds and AUMs are as of the end of a year. Fund returns and flows are averaged over the four quarters of a year. Percentage fund flows are cross-sectionally winsorized at the 1% and 99%. Panel C reports the summary statistics for fund characteristics, including quarterly percentage flows, total number of accounts, percentage change in number of accounts, average account size, fund age, percentage fee, fund idiosyncratic return volatility, fraction of foreign client assets, fraction of separate account assets, and fraction of accounts with assets below $10m. The distributional statistics reported include the mean, median, the first and third quartile, and standard deviation. These statistics are computed by pooling all fund-quarter observations.

Panel A: Summary statistics on sample investment advisory firms

Year	Number of Firms	Average Number of Funds Per Firm	Average Firm AUM ($m)	Number of Firms Managing Mutual Funds
2001	245	3.91	10,449.30	50
2002	342	3.96	6,905.81	78
2003	430	3.96	8,649.93	91
2004	490	4.02	9,412.80	73
2005	544	4.35	10,143.63	84
2006	622	4.35	11,147.63	106
2007	654	4.43	11,072.29	105
2008	640	4.44	6,038.92	104
2009	606	4.52	8,315.17	99
2010	613	4.28	9,604.84	113
2011	609	4.36	10,569.71	113

Panel B: Summary statistics on the institutional fund sample

Year	Number of Funds	Cross-sectional Mean AUM ($m)	Cross-sectional Mean Quarterly Return (%)	Cross-sectional Mean Quarterly Flow (%)	Cross-sectional Median AUM ($m)	Cross-sectional Median Quarterly Return (%)	Cross-sectional Median Quarterly Flow (%)
2001	673	2,230	1.95	4.71	764	0.82	1.56
2002	1,025	1,943	-4.31	3.92	547	-4.96	0.90
2003	1,326	1,893	8.76	4.59	621	8.19	1.20
2004	1,594	2,115	4.07	4.14	660	3.60	0.62
2005	1,833	2,098	1.94	3.02	627	1.94	0.02
2006	2,173	2,332	3.51	2.00	594	3.55	-0.43
2007	2,399	2,243	1.26	0.80	525	1.40	-0.99
2008	2,465	1,186	-10.89	-0.17	323	-10.66	-0.98
2009	2,338	1,624	7.16	-0.37	436	7.42	-1.14
2010	2,378	1,770	5.13	-1.10	486	4.89	-1.43
2011	2,247	2,042	7.12	0.36	566	6.84	-0.71

Panel C: Distribution of Fund Characteristics

Characteristics	NOBs	Mean	Median	Q1	Q3	Std. Dev.
Flow (%)	69,674	1.56	-0.39	-4.16	3.47	23.94
Number of accounts	66,043	314	15	5	50	6186
Change in number of accounts (%)	61,011	1.96	0.00	-2.27	2.22	20.11
Average account size ($m)	66,043	137.54	40.43	11.50	113.00	655.87
Age (Year)	69,674	13.92	13.00	8.00	19.00	7.84
Fee (%)	69,674	0.87	0.87	0.70	1.00	0.30
Volatility (%)	69,674	1.51	1.29	0.93	1.80	0.94
Percentage of foreign client assets (%)	15,804	6.72	0.00	0.00	0.94	18.80
Percentage of separate account assets (%)	53,583	68.59	92.08	32.74	100.00	38.45
Percentage of small accounts (%)	22,103	44.63	42.85	4.55	80.00	36.52

Table 2: Flow Response to Past Fund Performance

This table reports fund flow response to past performance. In each quarter we regress percentage fund flows onto the piecewise-linear functions of past fund performance (Lowperf, Midperf, and Highperf) as well as control variables. Past performance is measured by average fund return (Return), the four-factor alpha (Alpha), average fund return in excess of self-claimed benchmark (Benchmark-adj. Return), average fund return in excess of the average returns of all funds with the same investment style (Peer-adj. Return), information ratio, Sharpe ratio, and Treynor ratio, respectively. Past performance is measured during the past 12 months (Panel A) or past 36 months (Panel B). The control variables include the log fund age (Age), the log of fund assets (AUM), percentage fee (Fee), and idiosyncratic volatility from the four-factor model (Volatility). We report the time-series averages of the regression coefficients, the average difference in the estimated coefficients between Highperf and Lowperf (High-Low), the corresponding time-series t-statistics, and the average adjusted R-square of the regressions (Adj. R^2).

Panel A: One-year Performance Measures

	Return	Alpha	Benchmark-adj. Return	Peer-adj. Return	Information Ratio	Sharpe Ratio	Treynor Ratio
Intercept	0.075 (6.69)	0.074 (6.10)	0.070 (6.16)	0.070 (6.45)	0.083 (8.16)	0.069 (6.31)	0.072 (7.09)
Lowperf	0.217 (9.95)	0.225 (9.87)	0.210 (8.24)	0.198 (10.07)	0.164 (6.60)	0.226 (8.48)	0.212 (8.48)
Midperf	0.060 (8.51)	0.036 (4.69)	0.082 (11.30)	0.088 (14.82)	0.063 (9.06)	0.060 (9.28)	0.064 (10.04)
Highperf	0.240 (7.27)	0.208 (6.44)	0.212 (6.16)	0.175 (6.27)	0.243 (7.18)	0.237 (6.92)	0.210 (6.61)
Volatility	-0.797 (-3.94)	-0.451 (-2.31)	-0.533 (-2.47)	-0.522 (-2.55)	-0.659 (-3.56)	-0.389 (-1.98)	-0.583 (-3.29)
Ln(AUM)	-0.010 (-8.04)	-0.010 (-8.28)	-0.010 (-8.18)	-0.010 (-8.33)	-0.010 (-8.00)	-0.010 (-8.17)	-0.010 (-8.12)
Fee	-0.397 (-1.01)	0.091 (0.23)	-0.047 (-0.12)	0.149 (0.35)	-0.339 (-0.82)	-0.189 (-0.45)	-0.143 (-0.34)
Ln(Age)	-0.016 (-8.61)	-0.016 (-8.71)	-0.017 (-9.59)	-0.018 (-9.67)	-0.016 (-8.76)	-0.016 (-8.62)	-0.016 (-8.59)
Adj. R^2	0.038	0.030	0.044	0.042	0.036	0.038	0.036
High-Low	0.023 (0.56)	-0.017 (-0.47)	0.002 (0.05)	-0.023 (-0.68)	0.078 (1.60)	0.011 (0.23)	-0.002 (-0.05)

Panel B: Three-year Performance Measures

	Return	Alpha	Benchmark-adj. Return	Peer-adj. Return	Information Ratio	Sharpe Ratio	Treynor Ratio
Intercept	0.073 (5.59)	0.064 (4.70)	0.069 (5.15)	0.075 (6.72)	0.066 (5.38)	0.057 (4.92)	0.076 (6.46)
Lowperf	0.291 (13.42)	0.246 (9.41)	0.252 (11.92)	0.179 (6.89)	0.256 (10.59)	0.307 (15.18)	0.267 (12.80)
Midperf	0.069 (7.26)	0.094 (14.50)	0.112 (14.03)	0.115 (14.44)	0.089 (13.01)	0.073 (9.48)	0.072 (8.86)
Highperf	0.351 (9.33)	0.275 (8.00)	0.233 (7.45)	0.176 (6.57)	0.303 (8.56)	0.297 (8.78)	0.304 (8.18)
Ln(AUM)	-0.011 (-9.40)	-0.012 (-10.13)	-0.012 (-9.64)	-0.012 (-9.83)	-0.012 (-9.89)	-0.011 (-9.37)	-0.011 (-9.29)
Volatility	-1.696 (-7.37)	-1.139 (-6.53)	-1.333 (-5.75)	-1.107 (-4.90)	-1.226 (-8.05)	-0.961 (-6.87)	-1.501 (-8.58)
Fee	-0.591 (-1.63)	0.540 (1.28)	0.196 (0.47)	0.438 (1.06)	0.042 (0.10)	-0.358 (-0.85)	-0.793 (-2.12)
Ln(Age)	-0.014 (-8.56)	-0.014 (-8.67)	-0.016 (-9.67)	-0.016 (-9.56)	-0.014 (-8.75)	-0.014 (-8.46)	-0.014 (-8.64)
Adj. R^2	0.050	0.053	0.062	0.054	0.054	0.052	0.049
High-Low	0.060 (1.62)	0.029 (0.66)	-0.019 (-0.53)	-0.003 (-0.08)	0.047 (1.28)	-0.010 (-0.26)	0.038 (0.92)

Table 3: Flow Response to Multiple Performance Measures

This table reports fund flow response to multiple performance measures. In each quarter we regress percentage fund flows onto the piecewise-linear functions (Lowperf, Midperf, and Highperf) of multiple past fund performance measures as well as control variables. In Panel A, we include jointly the piecewise functions of the same performance measure over the past 12 months and over the past 36 months. In Panel B, we include jointly the piecewise functions of the four return-based performance measures – Return, Alpha, Benchmark-adj. Return, and Peer-adj. Return. In Panel C, we include jointly the piecewise functions of the three ratio-based performance measures – information ratio (IR), Sharpe ratio (SR), and Treynor ratio (TR). Performance measures in Panels B and C are over past 36 months. The control variables include the log fund age (Age), the log of fund assets (AUM), percentage fee (Fee), and idiosyncratic volatility from the four-factor model (Volatility). We report the time-series averages of the regression coefficients, the corresponding time-series t-statistics, and the average adjusted R-square of the regressions.

Panel A: One-year vs. Three-year Performance Measures							
	Return	Alpha	Benchmark-adj. Return	Peer-adj. Return	Information Ratio	Sharpe Ratio	Treynor Ratio
Intercept	0.056 (4.37)	0.044 (3.27)	0.042 (3.51)	0.065 (5.68)	0.049 (4.34)	0.043 (4.15)	0.054 (5.19)
Lowperf 1y	0.114 (4.39)	0.115 (4.91)	0.074 (2.90)	-0.010 (-0.17)	0.081 (2.94)	0.101 (3.42)	0.117 (4.25)
Midperf 1y	0.022 (2.45)	0.003 (0.41)	0.040 (6.21)	0.037 (3.86)	0.032 (4.54)	0.010 (1.21)	0.022 (2.68)
Highperf 1y	0.108 (3.04)	0.080 (2.47)	-0.075 (-2.48)	0.019 (0.53)	0.140 (4.20)	0.118 (3.26)	0.106 (3.06)
Lowperf 3y	0.235 (9.50)	0.221 (8.03)	0.201 (9.08)	0.187 (2.73)	0.226 (9.11)	0.265 (11.50)	0.223 (9.95)
Midperf 3y	0.055 (5.26)	0.090 (14.37)	0.106 (13.21)	0.099 (7.45)	0.078 (11.93)	0.066 (7.98)	0.065 (7.83)
Highperf 3y	0.325 (8.49)	0.258 (7.81)	0.043 (1.27)	0.008 (0.20)	0.272 (7.82)	0.278 (8.66)	0.277 (7.14)
Volatility 1y	-0.596 (-2.64)	-0.387 (-1.63)	-0.414 (-2.02)	-0.481 (-2.38)	-0.299 (-1.33)	-0.442 (-1.90)	-0.570 (-2.45)
Volatility 3y	-1.086 (-4.12)	-0.616 (-2.29)	-0.615 (-2.87)	-0.782 (-3.41)	-0.982 (-3.96)	-0.485 (-2.11)	-0.871 (-3.62)
Ln(AUM)	-0.011 (-9.00)	-0.011 (-9.82)	-0.011 (-9.47)	-0.011 (-9.76)	-0.011 (-9.45)	-0.011 (-9.24)	-0.011 (-9.15)
Fee	-0.326 (-0.81)	0.488 (1.18)	0.705 (1.76)	0.905 (2.28)	0.017 (0.04)	-0.204 (-0.47)	-0.357 (-0.89)
Ln(Age)	-0.014 (-8.38)	-0.014 (-8.35)	-0.016 (-9.09)	-0.015 (-8.85)	-0.014 (-8.45)	-0.014 (-8.27)	-0.014 (-8.28)
Adj. R^2	0.056	0.058	0.058	0.051	0.062	0.057	0.056

Panel B: Return-based measures		Panel C: Ratio-based measures	
Intercept	0.031 (2.63)	Intercept	0.037 (3.44)
Lowperf – Return	0.127 (4.48)	Lowperf – IR	0.213 (6.61)
Lowperf – Alpha	0.071 (2.79)	Lowperf – SR	0.294 (3.33)
Lowperf – Benchmark-adj. Return	0.112 (4.42)	Lowperf – TR	-0.119 (-1.25)
Lowperf – Peer-adj. Return	0.061 (1.91)		
Midperf – Return	0.005 (0.54)	Midperf – IR	0.060 (7.60)
Midperf – Alpha	0.044 (7.46)	Midperf – SR	0.035 (1.84)
Midperf – Benchmark-adj. Return	0.056 (5.90)	Midperf – TR	-0.011 (-0.28)
Midperf – Peer-adj. Return	0.041 (5.09)		
Highperf – Return	0.131 (3.78)	Highperf – IR	0.210 (5.20)
Highperf – Alpha	0.193 (5.13)	Highperf – SR	0.122 (2.10)
Highperf – Benchmark-adj. Return	-0.060 (-2.03)	Highperf – TR	0.069 (0.62)
Highperf – Peer-adj. Return	0.009 (0.33)		
Volatility	-1.646 (-7.32)	Volatility	-1.235 (-6.75)
Ln(AUM)	-0.012 (-10.20)	Ln(AUM)	-0.011 (-9.81)
Fee	0.696 (1.56)	Fee	0.364 (0.85)
Ln(Age)	-0.014 (-8.67)	Ln(Age)	-0.013 (-8.46)
Adj. R^2	0.071	Adj. R^2	0.064

Table 4: Responses by Percentage Change of Accounts to Past Performance

This table reports the responses to past performance by the percentage changes in the number of accounts of institutional funds. In each quarter we regress percentage change of the number of accounts onto the piecewise-linear functions of past fund performance (Lowperf, Midperf, and Highperf) as well as control variables. Fund performance is measured over the past 36 months, by average fund return (Return), the four-factor alpha (Alpha), average fund return in excess of self-claimed benchmark (Benchmark-adj. Return), average fund return in excess of the average returns of all funds with the same investment style (Peer-adj. Return), information ratio, Sharpe ratio, and Treynor ratio, respectively. The control variables include the log fund age (Age), the log of fund assets (AUM), percentage fee (Fee), and idiosyncratic volatility from the four-factor model (Volatility). We report the time-series averages of the regression coefficients, the average difference in the estimated coefficients between Highperf and Lowperf (High-Low), the corresponding time-series t-statistics, and the average adjusted R-square of the regressions.

	Return	Alpha	Benchmark-adj. Return	Peer-adj. Return	Information Ratio	Sharpe Ratio	Treynor Ratio
Intercept	0.047 (3.80)	0.049 (3.78)	0.055 (4.23)	0.064 (5.02)	0.052 (4.01)	0.038 (3.02)	0.051 (4.11)
Lowperf	0.290 (11.95)	0.202 (8.71)	0.195 (7.20)	0.109 (4.15)	0.191 (7.37)	0.260 (9.87)	0.258 (10.56)
Midperf	0.067 (9.57)	0.087 (10.43)	0.108 (16.94)	0.109 (16.64)	0.089 (9.88)	0.085 (14.29)	0.075 (14.20)
Highperf	0.301 (8.15)	0.219 (7.01)	0.187 (6.81)	0.147 (4.06)	0.207 (5.55)	0.193 (6.05)	0.237 (6.97)
Volatility	-1.608 (-6.38)	-1.111 (-5.14)	-1.335 (-4.93)	-1.160 (-4.52)	-1.101 (-6.40)	-0.925 (-6.61)	-1.431 (-7.14)
Ln(AUM)	-0.007 (-4.88)	-0.007 (-5.53)	-0.007 (-5.35)	-0.007 (-5.43)	-0.007 (-5.39)	-0.006 (-4.71)	-0.006 (-4.68)
Fee	0.130 (0.23)	1.232 (2.21)	0.956 (1.67)	1.100 (2.15)	0.808 (1.49)	0.321 (0.54)	-0.060 (-0.11)
Ln(Age)	-0.013 (-5.77)	-0.013 (-5.78)	-0.016 (-6.77)	-0.015 (-6.67)	-0.013 (-5.82)	-0.013 (-5.65)	-0.013 (-5.85)
Adj. R^2	0.039	0.037	0.044	0.039	0.038	0.039	0.036
High-Low	0.012 (0.28)	0.017 (0.47)	-0.009 (-0.19)	0.038 (0.92)	0.016 (0.46)	-0.067 (-1.74)	-0.021 (-0.53)

Table 5: Flow Response to Past Performance: Effect of Investor Search Costs

This table reports the effect of investor search costs on the relation between fund flows and past performance. The fund characteristic variables (Char) related to investor search costs are 1) an indicator Large Family, for funds affiliated with the top tercile of fund families in terms of number of funds; 2) Mutual Fund Firm, for funds managed by mutual fund advisory firms; 3) Foreign Clients, for funds with proportion of assets from foreign clients ranked in the top tercile across funds; and 4) Star Firm, for funds managed by the top tercile advisory firms in terms of the percentage of top-performing funds. In each quarter we perform cross-sectional regressions, with the dependent variable being the percentage fund flow. In Panel A, the main explanatory variables are Alpha Rank, the cross-sectional percentile rank of the four-factor alpha during the past 36 months; Char, one of the fund characteristics related to investor search costs; and the product term of Alpha Rank and Char. In Panel B, the main explanatory variables include the three piecewise linear function of Alpha Rank (Lowperf, Midperf, and Highperf), Char, and the product terms of the piecewise linear functions of Alpha Rank with Char. The control variables include the idiosyncratic volatility from the four-factor model (Volatility), the log of fund assets (AUM), percentage fee (Fee), and the log fund age (Age). We report the time-series averages of the regression coefficients, the corresponding time-series t-statistics, and the average adjusted R-square of the regressions.

Panel A

	Large Family	Mutual Fund Firm	Foreign Clients	Star Family
Intercept	0.102 (7.18)	0.107 (7.33)	0.112 (7.56)	0.112 (7.48)
Alpha Rank	0.133 (23.69)	0.121 (19.73)	0.118 (19.76)	0.113 (17.97)
Char	0.017 (3.90)	0.003 (0.69)	0.021 (4.96)	-0.005 (-0.81)
Alpha Rank*Char	-0.021 (-2.70)	0.005 (0.54)	0.007 (1.14)	0.018 (2.41)
Volatility	-0.983 (-5.86)	-0.995 (-5.85)	-0.998 (-5.87)	-1.119 (-6.51)
Ln(AUM)	-0.011 (-8.20)	-0.010 (-9.29)	-0.012 (-9.76)	-0.010 (-8.97)
Fee	0.554 (1.27)	0.318 (0.75)	0.219 (0.51)	0.381 (0.90)
Ln(Age)	-0.029 (-12.54)	-0.029 (-13.14)	-0.027 (-12.57)	-0.029 (-13.51)
Adj. R^2	0.056	0.055	0.058	0.055

Panel B

	Large Family	Mutual Fund Firm	Foreign Clients	Star Family
Intercept	0.103 (6.88)	0.093 (5.64)	0.096 (5.69)	0.096 (5.81)
Lowperf	0.237 (6.80)	0.250 (8.19)	0.267 (7.88)	0.234 (7.45)
Midperf	0.077 (8.20)	0.083 (11.77)	0.075 (8.98)	0.090 (12.87)
Highperf	0.366 (7.66)	0.288 (7.80)	0.299 (7.28)	0.224 (2.49)
Char	-0.010 (-1.44)	0.005 (0.52)	0.033 (3.52)	0.000 (-0.02)
Lowperf*Char	-0.002 (-0.05)	-0.026 (-0.46)	-0.089 (-1.60)	0.018 (0.24)
Midperf*Char	0.020 (1.77)	0.023 (1.96)	0.032 (2.61)	-0.004 (-0.23)
Highperf*Char	-0.203 (-4.19)	-0.124 (-1.79)	-0.093 (-2.09)	0.046 (0.52)
Volatility	-1.135 (-6.19)	-1.024 (-5.58)	-1.032 (-5.60)	-1.062 (-5.78)
Ln(AUM)	-0.010 (-9.09)	-0.010 (-9.47)	-0.012 (-9.96)	-0.010 (-9.15)
Fee	0.375 (0.92)	0.343 (0.82)	0.214 (0.51)	0.406 (0.98)
Ln(Age)	-0.030 (-13.39)	-0.029 (-12.95)	-0.027 (-12.34)	-0.029 (-13.49)
Adj. R^2	0.057	0.057	0.060	0.057

Table 6: Flow Response to Past Performance: Effect of Liquidity Sharing

This table reports the effect of lack of liquidity sharing on the relation between fund flows and past performance. The fund characteristic variables (Char) related to liquidity sharing are 1) an indicator variable Separate Accounts, for funds with fraction of separate account assets in AUM ranked in the top tercile across all funds; 2) an indicator variable Average Account Size, for funds whose average account size ranked in the top tercile across funds; and 3) an indicator variable Small Accounts, for funds with the fraction of small accounts (with assets below $10m) ranked in the top tercile across funds. In each quarter we perform cross-sectional regressions, with the dependent variable being the percentage fund flow. In Panel A, the main explanatory variables are Alpha Rank, the cross-sectional percentile rank of the four-factor alpha during the past 36 months; Char, one of the fund characteristics related to investor search costs; and the product term of Alpha Rank and Char. In Panel B, the main explanatory variables include the three piecewise linear function of Alpha Rank (Lowperf, Midperf, and Highperf), Char, and the product terms of the piecewise linear functions of Alpha Rank with Char. The control variables include the idiosyncratic volatility from the four-factor model (Volatility), the log of fund assets (AUM), percentage fee (Fee), and the log fund age (Age). We report the time-series averages of the regression coefficients, the corresponding time-series t-statistics, and the average adjusted R-square of the regressions.

Panel A

	Separate Accounts	Average Account Size	Small Accounts
Intercept	0.112 (7.05)	0.101 (7.05)	0.126 (7.27)
Alpha Rank	0.130 (18.34)	0.131 (21.08)	0.116 (16.33)
Char	-0.003 (-0.72)	0.004 (1.21)	-0.007 (-1.37)
Alpha Rank*Char	-0.010 (-1.24)	-0.029 (-4.26)	0.004 (0.51)
Volatility	-0.938 (-5.40)	-1.004 (-6.09)	-0.873 (-4.14)
Ln(AUM)	-0.011 (-9.59)	-0.009 (-8.37)	-0.014 (-9.61)
Fee	-0.101 (-0.16)	0.315 (0.76)	0.065 (0.11)
Ln(Age)	-0.029 (-11.49)	-0.030 (-13.90)	-0.023 (-10.79)
Adj. R^2	0.055	0.055	0.057

Panel B

	Separate Accounts	Average Account Size	Small Accounts
Intercept	0.093 (5.27)	0.091 (5.41)	0.123 (6.32)
Lowperf	0.288 (9.63)	0.236 (6.98)	0.195 (4.80)
Midperf	0.093 (10.33)	0.096 (12.33)	0.080 (8.32)
Highperf	0.257 (7.38)	0.277 (6.80)	0.322 (7.16)
Char	0.010 (1.24)	-0.002 (-0.20)	-0.020 (-2.54)
Lowperf*Char	-0.094 (-2.09)	0.001 (0.02)	0.094 (2.25)
Midperf*Char	-0.001 (-0.03)	-0.025 (-2.34)	-0.004 (-0.32)
Highperf*Char	0.002 (0.02)	-0.053 (-1.27)	-0.006 (-0.08)
Volatility	-0.979 (-5.06)	-1.041 (-5.77)	-1.081 (-4.61)
Ln(AUM)	-0.011 (-10.00)	-0.009 (-8.58)	-0.014 (-9.68)
Fee	-0.063 (-0.10)	0.341 (0.84)	0.002 (0.00)
Ln(Age)	-0.029 (-11.35)	-0.030 (-13.72)	-0.023 (-10.79)
Adj. R^2	0.057	0.056	0.060

Table 7: Flow Response to Past Performance: Effect of Investment Illiquidity

This table reports the effect of fund investment illiquidity on the relation between fund flows and past performance. The fund characteristic variables (Char) related to investment illiquidity are 1) an indicator variable for Smallcap funds; 2) an indicator variable Illiquidity Beta, for funds with illiquidity beta ranked in the top tecile across funds; and 3) an indicator variable Pricing Frequency, for funds with less than daily pricing frequencies. In each quarter we perform cross-sectional regressions, with the dependent variable being the percentage fund flow. In Panel A, the main explanatory variables are Alpha Rank, the cross-sectional percentile rank of the four-factor alpha during the past 36 months; Char, one of the fund characteristics related to investor search costs; and the product term of Alpha Rank and Char. In Panel B, the main explanatory variables include the three piecewise linear function of Alpha Rank (Lowperf, Midperf, and Highperf), Char, and the product terms of the piecewise linear functions of Alpha Rank with Char. The control variables include the idiosyncratic volatility from the four-factor model (Volatility), the log of fund assets (AUM), percentage fee (Fee), and the log fund age (Age). We report the time-series averages of the regression coefficients, the corresponding time-series t-statistics, and the average adjusted R-square of the regressions.

Panel A

	Smallcap Funds	Illiquidity Beta	Pricing Frequency
Intercept	0.107 (7.43)	0.106 (7.23)	0.107 (6.81)
Alpha Rank	0.122 (18.80)	0.125 (19.32)	0.128 (17.58)
Char	-0.007 (-1.32)	-0.009 (-2.28)	0.001 (0.27)
Alpha Rank*Char	0.009 (1.03)	-0.003 (-0.47)	-0.008 (-1.21)
Volatility	-0.974 (-6.07)	-0.859 (-4.91)	-1.001 (-5.92)
Ln(AUM)	-0.010 (-9.21)	-0.010 (-9.21)	-0.010 (-9.25)
Fee	0.556 (1.33)	0.532 (1.21)	0.410 (0.96)
Ln(Age)	-0.029 (-13.67)	-0.030 (-13.80)	-0.029 (-13.42)
Adj. R^2	0.055	0.055	0.054

Panel B

	Smallcap Funds	Illiquidity Beta	Pricing Frequency
Intercept	0.093 (7.19)	0.089 (5.39)	0.085 (4.69)
Lowperf	0.226 (8.19)	0.254 (6.62)	0.315 (7.30)
Midperf	0.102 (12.81)	0.103 (12.55)	0.083 (7.78)
Highperf	0.208 (5.19)	0.187 (4.19)	0.279 (5.84)
Char	-0.008 (-0.86)	-0.005 (-0.54)	0.016 (1.84)
Lowperf*Char	0.081 (1.46)	0.020 (0.42)	-0.119 (-2.39)
Midperf*Char	-0.037 (-3.24)	-0.044 (-5.47)	0.008 (0.76)
Highperf*Char	0.138 (2.76)	0.209 (3.90)	-0.012 (-0.24)
Volatility	-1.026 (-5.89)	-0.900 (-4.78)	-1.052 (-5.76)
Ln(AUM)	-0.010 (-9.51)	-0.010 (-9.46)	-0.010 (-9.49)
Fee	0.575 (1.41)	0.554 (1.28)	0.414 (1.00)
Ln(Age)	-0.029 (-13.55)	-0.030 (-13.39)	-0.029 (-13.35)
Adj. R^2	0.057	0.058	0.057

Table 8: Flow Response to Past Performance: Joint Effects of Investment Illiquidity and Liquidity Sharing

This table reports the joint effects of fund investment illiquidity and lack of liquidity sharing on the relation between fund flows and past performance. The fund characteristic variables related to investment illiquidity (ILLIQ) are 1) an indicator variable for Smallcap funds; 2) an indicator variable Illiquidity Beta, for funds with illiquidity beta ranked in the top tecile across funds; and 3) an indicator variable Pricing Frequency, for funds with less than daily valuation frequencies. The fund characteristic variables related to liquidity sharing (SHARE) are 1) an indicator variable Separate Accounts, for funds with fraction of separate account assets in AUM ranked in the top tercile across all funds; 2) an indicator variable Average Account Size, for funds whose average account size ranked in the top tercile across funds; and 3) an indicator variable Small Accounts, for funds with the fraction of small accounts (with assets below $10m) ranked in the top tercile across funds. In each quarter we perform cross-sectional regressions, with the dependent variable being the percentage fund flow. The main explanatory variables include ILLIQ, SHARE, the three piecewise linear function of Alpha Rank (Lowperf, Midperf, and Highperf), and their respective product terms with ILLIQ and SHARE. The control variables include the idiosyncratic volatility from the four-factor model (Volatility), the log of fund assets (AUM), percentage fee (Fee), and the log fund age (Age). We report the time-series averages of the regression coefficients, the corresponding time-series t-statistics, and the average adjusted R-square of the regressions.

ILLIQ	Smallcap Funds			Illiquidity Beta			Pricing Frequency		
SHARE	Separate Accounts	Avg. Acct. Size	Small Accounts	Separate Accounts	Avg. Acct. Size	Small Accounts	Separate Accounts	Avg. Acct. Size	Small Accounts
Intercept	0.089 (6.34)	0.091 (6.93)	0.130 (7.83)	0.087 (5.16)	0.085 (5.03)	0.120 (5.94)	0.083 (4.24)	0.083 (4.40)	0.110 (5.19)
Lowperf	0.289 (6.24)	0.211 (7.93)	0.134 (3.63)	0.300 (8.55)	0.253 (6.00)	0.196 (3.66)	0.368 (10.52)	0.304 (6.00)	0.293 (4.92)
Midperf	0.107 (11.65)	0.113 (12.60)	0.095 (8.54)	0.113 (11.08)	0.110 (12.08)	0.093 (8.64)	0.079 (7.92)	0.091 (7.59)	0.076 (6.30)
Highperf	0.206 (5.85)	0.212 (4.50)	0.274 (5.31)	0.158 (3.15)	0.196 (3.95)	0.235 (3.89)	0.331 (5.80)	0.289 (5.17)	0.326 (5.11)
ILLIQ	-0.004 (-0.32)	-0.009 (-0.96)	-0.025 (-2.81)	0.002 (0.18)	-0.002 (-0.18)	-0.014 (-1.09)	0.016 (2.27)	0.015 (1.68)	0.026 (2.56)
SHARE	0.008 (1.13)	-0.005 (-0.61)	-0.024 (-3.02)	0.010 (1.27)	-0.002 (-0.25)	-0.020 (-2.55)	0.012 (1.51)	-0.003 (-0.42)	-0.020 (-2.41)
Lowperf*ILLIQ	0.062 (0.85)	0.088 (1.61)	0.152 (2.75)	0.000 (-0.01)	0.002 (0.04)	0.047 (0.69)	-0.128 (-3.51)	-0.114 (-2.24)	-0.170 (-2.76)
Midperf*ILLIQ	-0.040 (-3.52)	-0.038 (-3.34)	-0.036 (-2.90)	-0.054 (-4.96)	-0.042 (-5.30)	-0.036 (-3.54)	0.023 (1.93)	0.009 (0.82)	0.007 (0.57)
Highperf*ILLIQ	0.112 (1.87)	0.133 (2.64)	0.083 (1.47)	0.255 (3.63)	0.205 (3.93)	0.193 (2.80)	-0.114 (-1.38)	-0.014 (-0.29)	-0.008 (-0.14)
Lowperf*SHARE	-0.086 (-2.13)	0.025 (0.50)	0.111 (2.04)	-0.096 (-2.10)	0.002 (0.05)	0.088 (1.96)	-0.110 (-2.33)	0.011 (0.21)	0.093 (1.77)
Midperf*SHARE	0.000 (0.00)	-0.029 (-2.79)	-0.008 (-0.63)	0.001 (0.03)	-0.023 (-2.16)	-0.007 (-0.49)	0.001 (0.04)	-0.025 (-2.33)	-0.004 (-0.26)
Highperf*SHARE	0.004 (0.06)	-0.032 (-0.75)	0.004 (0.05)	-0.024 (-0.26)	-0.054 (-1.39)	0.009 (0.12)	-0.011 (-0.13)	-0.058 (-1.39)	-0.008 (-0.12)
Volatility	-0.934 (-4.81)	-1.015 (-5.88)	-0.989 (-4.24)	-0.808 (-3.89)	-0.895 (-4.81)	-0.852 (-3.70)	-0.970 (-5.03)	-1.038 (-5.77)	-1.085 (-4.71)
Ln(AUM)	-0.011 (-10.13)	-0.009 (-8.58)	-0.014 (-9.81)	-0.011 (-10.21)	-0.009 (-8.61)	-0.014 (-9.83)	-0.011 (-9.71)	-0.009 (-8.64)	-0.014 (-9.74)
Fee	0.098 (0.17)	0.467 (1.16)	0.252 (0.48)	-0.022 (-0.03)	0.445 (1.05)	0.141 (0.26)	-0.109 (-0.17)	0.309 (0.76)	-0.054 (-0.10)
Ln(Age)	-0.029 (-11.77)	-0.030 (-14.02)	-0.023 (-10.83)	-0.029 (-11.39)	-0.030 (-13.82)	-0.023 (-10.51)	-0.028 (-11.41)	-0.030 (-13.77)	-0.023 (-10.89)
Adj. R^2	0.057	0.057	0.061	0.059	0.058	0.062	0.056	0.057	0.061

Table 9: Flow Response to Past Performance: Joint Effects of Investment Illiquidity, Liquidity Sharing, and Search Costs

This table reports the joint effects of fund investment illiquidity, lack of liquidity sharing, and investor search costs on the relation between fund flows and past performance. The fund characteristic variables include ILLIQ, SHARE, and SEARCH, combined measures of investment illiquidity, lack of liquidity sharing, and search costs. In each quarter we perform cross-sectional regressions, with the dependent variable being the percentage fund flow. The main explanatory variables include ILLIQ, SHARE, the three piecewise linear function of Alpha Rank (Lowperf, Midperf, and Highperf), and their respective product terms with ILLIQ and SHARE. The control variables include the idiosyncratic volatility from the four-factor model (Volatility), the log of fund assets (AUM), percentage fee (Fee), and the log fund age (Age). We report the time-series averages of the regression coefficients, the corresponding time-series t-statistics, and the average adjusted R-square of the regressions.

Intercept	0.106 (4.97)
ILLIQ	-0.005 (-0.33)
SHARE	0.026 (1.88)
SEARCH	-0.036 (-2.48)
Lowperf	0.253 (2.44)
Midperf	0.111 (6.68)
Highperf	0.316 (2.59)
Lowperf*ILLIQ	0.025 (0.27)
Midperf*ILLIQ	-0.070 (-3.53)
Highperf*ILLIQ	0.304 (2.88)
Lowperf*SHARE	-0.140 (-2.19)
Midperf*SHARE	-0.055 (-2.79)
Highperf*SHARE	-0.001 (-0.01)
Lowperf*SEARCH	0.075 (0.85)
Midperf*SEARCH	0.068 (3.63)
Highperf*SEARCH	-0.313 (-2.65)
Volatility	-1.002 (-5.45)
Ln(AUM)	-0.010 (-9.01)
Fee	0.586 (1.38)
Ln(Age)	-0.030 (-14.26)
Adj. R^2	0.061

Table 10: Fund Flows and Future Performance

This table reports the results of the cross-sectional regressions for the relation between fund flows and future fund performance. The dependent variable is the monthly fund abnormal return based on the Carhart four-factor model. The main explanatory variables are either the cross-sectional quintile rank of quarterly fund flow or the positive and negative parts of the quarterly flows (Positive flow and Negative flow). In Panel A, fund flow is the percentage flow. In Panel B, fund flow is the percentage change in the number of accounts. The control variables include lagged fund four-factor alpha (Lagged α), the log of fund assets (AUM), idiosyncratic volatility from the four-factor model (Volatility), percentage fee (Fee), and the log fund age (Age). Future fund abnormal returns are measured at three different horizons: subsequent 1 to 3 months, 1 to 12 months, and 13 to 24 months. We report the time-series averages of the estimated coefficients and the corresponding time-series t-statistics.

Panel A: Explanatory variable(s) based on percentage flow						
Horizon	Months 1-3		Months 1-12		Months 13-24	
Intercept	0.652 (1.71)	0.595 (1.57)	0.680 (2.96)	0.641 (2.78)	0.701 (2.77)	0.669 (2.63)
Flow Rank	-0.017 (-2.14)		-0.012 (-3.01)		-0.015 (-3.83)	
Positive Flow		-0.015 (-0.49)		-0.014 (-0.81)		-0.058 (-5.17)
Negative Flow		-0.142 (-1.66)		-0.103 (-2.25)		-0.078 (-1.73)
Lagged alpha	0.111 (1.36)	0.095 (1.20)	0.082 (2.54)	0.071 (2.26)	0.142 (3.15)	0.135 (2.95)
Volatility	-0.519 (-0.06)	-0.337 (-0.04)	0.589 (0.16)	0.757 (0.21)	2.211 (0.61)	2.268 (0.63)
Log(AUM) (x10^2)	-2.115 (-2.77)	-2.059 (-2.70)	-1.598 (-3.56)	-1.536 (-3.43)	-0.491 (-1.25)	-0.523 (-1.37)
Fee	-0.281 (-1.16)	-0.273 (-1.13)	-0.339 (-2.97)	-0.338 (-2.98)	-0.346 (-2.91)	-0.347 (-2.92)
Log(Age) (x10^2)	-3.652 (-2.37)	-3.247 (-2.08)	-3.470 (-5.28)	-3.276 (-4.90)	-2.762 (-3.81)	-2.577 (-3.60)
Panel B: Explanatory variable(s) based on percentage change of accounts						
Horizon	Months 1-3		Months 1-12		Months 13-24	
Intercept	0.615 (1.61)	0.603 (1.59)	0.666 (2.91)	0.654 (2.87)	0.702 (2.77)	0.665 (2.62)
Percentage Acct Change Rank	-0.007 (-0.74)		-0.006 (-1.41)		-0.017 (-5.20)	
Positive Percentage Acct Change		-0.086 (-1.51)		-0.046 (-2.50)		-0.078 (-4.31)
Negative Percentage Acct Change		-0.017 (-0.15)		-0.009 (-0.17)		-0.104 (-2.96)
Lagged alpha	0.105 (1.29)	0.100 (1.25)	0.071 (2.19)	0.067 (2.11)	0.149 (3.17)	0.144 (3.06)
Volatility	-0.990 (-0.11)	-0.894 (-0.10)	0.777 (0.21)	0.785 (0.21)	2.038 (0.55)	2.148 (0.58)
Log(AUM) (x10^2)	-2.071 (-2.59)	-2.003 (-2.47)	-1.576 (-3.77)	-1.570 (-3.73)	-0.458 (-1.24)	-0.470 (-1.28)
Fee	-0.350 (-1.39)	-0.356 (-1.42)	-0.389 (-3.48)	-0.387 (-3.45)	-0.289 (-2.40)	-0.298 (-2.45)
Log(Age) (x10^2)	-2.360 (-1.78)	-2.444 (-1.85)	-3.062 (-4.80)	-3.024 (-4.62)	-3.069 (-4.00)	-3.897 (-3.78)

Figure 1: Fund Flows Across Performance Deciles

This figure plots the percentage fund flows against cross-sectional decile ranks of past fund performance. Past fund performance is measured by the four-quarter average return or the 36-month four-factor alpha.