Understanding the Non-linear Relation between Mutual Fund Performance and Flows

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Abstract

We examine gross flows to mutual funds and find that existing investors punish poorly performing funds by increasing outflows. We also find that existing and potential investors punish poorly performing funds by reducing inflows. Finally, we uncover that current investors respond to poor performance with the same intensity as they do to good performance. Overall, we conclude that new investors must drive the observed non-linearity between mutual fund performance and net flows. This conclusion runs contrary to the extant literature which generally ascribes the absence of net outflows in the face of poor performance to inactivity by existing fund investors (i.e., they do not exit).

The non-linear relation between annual mutual fund performance and subsequent annual net flows is perhaps one of the best documented empirical regularities in mutual fund research [Ippolito (1992), Chevalier and Ellison (1997), Sirri and Tufano (1998), Del Guercio and Tkac (2002)]. Net flows are typically found to be positively correlated with past fund performance but only for funds at the high end of the performance rankings spectrum: conversely, no association or, a very weak association is found for medium and low performing funds.[1] Recent research proposes two frameworks for understanding the non-linearity between mutual fund performance and flows.

The first framework motivates asymmetry by arguing that existing fund investors do not respond to poor performance [Gruber (1996), Lynch and Musto (2003), and Ivkovic and Weisbenner (2006)]. These papers suggest that investors may not respond to poor performance for several possible reasons, such as trading frictions, expectations of a change in management, or behavioral biases. The second theoretical framework for understanding the non-linear performance-flow relation focuses on the reactions of new investors to top performance. Although this line of research is less well developed, Huang, Wei, and Yan (2007), for example, argue that new investors are relatively better able to overcome their participation costs and respond to good performance inducing the non-linear relation between performance and flows.

In this paper, we examine the relation between fund performance, and the subsequent gross flows (outflows and inflows) to the fund in an attempt to understand what drives the non-linearity in the performance–net flow relation. Ours is not the first paper to attempt to understand the non-linearity, however the earliest work examining the role of existing and new investors in the performance flow relation could only speculate about investor actions because disaggregated

[1] Chevalier and Ellison (1997) find evidence of outflows in response to poor performance among the youngest

inflow and outflow data were not available. More recently, researchers have begun to analyze disaggregated flow data. Results from these papers appear to be consistent with the view that investors do not react to poor performance. Or, at least, investors do not react to the type of risk-adjusted performance previous studies have adopted while uncovering the non-linear performance-flow relation. Bergstresser and Poterba (2002) find no relation between prior returns (adjusted for the sample mean) and outflows (see their Table XII). Ivkovic and Weisbenner (2006) use account level data and find evidence that the propensity to sell is related to performance relative to other funds with the same investment objective (see their Table III), but the effect is small in economic terms. More importantly, however, Ivkovic and Weisbenner (2006) find that current outflows are not affected by prior year peer adjusted returns (see their Table VII). Similarly, Johnson (2005) examines daily inflows and outflows for a small mutual fund family and finds that outflows are not affected by poor prior performance.[2]

Our research proceeds as follows. First, we replicate the previously documented non-linear relation between performance and *net* flows. This result gives us a starting point that is similar to that documented in the prior literature—namely, that investors, on net, respond to good performance, but are relatively indifferent to average or poor performance.

We next demonstrate that there is an unconditional U-shaped relation between performance and fund outflows.[3] In other words, we find that investors do respond to poor performance by withdrawing more money from poorly performing funds. However, we also find that funds with good performance experience greater outflows. Put differently, our unconditional analysis suggests that current investors withdraw assets from both the worst and the best performing

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mutual funds, but no relation between outflows and performance for older funds.

[2] A notable exception is Christoffersen, Evans and Musto (2005). They find that outflows increase in response to both good and bad performance. We discuss their findings in greater detail in Section 3.3.

[3] Christoffersen, Evans, and Musto (2005) document a similar result.

funds.

We next examine the unconditional relation between performance and fund inflows. Consistent with prior research, we find that current and potential investors reward good performance with increased inflows. Similar to the outflow relation, though, we find evidence of a U-shaped relation between performance and inflows—in addition to rewarding good performance, investors also appear to reward (with increased inflows) funds whose performance is poor. Overall, our unconditional analysis yields both expected and unexpected results.

We next explore the relation between performance and gross flows in a conditional setting. Recent research suggests that there is considerable persistence in mutual fund flows [Del Guercio and Tkac (2002), Cashman, Deli, Nardari, and Villupuram (2006)]. When we control for the persistence in outflows we continue to find evidence that current investors punish poorly performing mutual funds by withdrawing money from those funds, but we no longer find any relation between performance and outflows for the best performing funds. Similarly, when we examine inflows controlling for their persistence we find that current and potential investors respond favorably to good performance, but appear to be indifferent to poor performance.

The results obtained while controlling for the flow persistence are more intuitively appealing than the results in the unconditional analysis, but they do raise the questions of why outflows don't decline in the face of good performance and why inflows don't decrease in the face of bad performance. O'Neal (2004) argues that some investors trade in and out of mutual funds within a year and finds that inferences about gross annual flows are sensitive to the inclusion of flows in the opposite direction. Additionally, recent research suggests that potentially some investors trade in and out of mutual funds at a much higher frequency.[4]

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[4] Bhargava and Dubofsky (2001), Chalmers, Edelen and Kadlec (2001), Goetzman, Ivkovic and Rouwenhorst

Together, these findings suggest the potential importance of controlling for concurrent inflows when examining outflows and vice versa when examining inflows.[5] When we control for such trading, we continue to find that investors punish poor performance by withdrawing funds and reward good performance by increasing inflows. Unlike our prior results, however, we find that current and potential investors respond to bad performance by reducing their purchases and that current investors respond to good performance by reducing their outflows. In other words, not only do current investors punish poor performance by increasing their outflows, but they also reward good performance by reducing their outflows.

The result that investors punish funds for poor performance is important for several reasons. First, it gives us broader insight into the trading decisions of mutual fund investors. Prior researchers have pondered the apparent lack of response to poor fund performance and attributed it to a lack of response by current investors. Our research shows that investors do respond to poor performance; current investors remove money from the funds, while current and potential investors reduce their purchases of fund shares. These results are quite different from those of Bergstresser and Poterba (2002) and Ivkovic and Weisbenner (2006). Neither of these studies finds a relation between (relative) performance and outflows. Thus, our results highlight a previously unrecognized aspect of decision making by mutual fund investors.

In demonstrating that investors respond to poor performance by withdrawing funds, we provide indirect support for the theoretical framework of Huang, Wei, and Yan (2007). As noted earlier, Huang, Wei, and Yan (2007) contend that new investors coming into the fund drive the non-linearity in the relation between mutual fund performance and net flows. Because we are

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(2001), Greene and Hodges (2002), and Zitzewitz (2003)

[5] Specifically, in a base linear regression, O'Neal (2004) finds that the coefficient on the relation between performance and outflows changes sign with the inclusion of concurrent inflows in the regression.

able to isolate the decisions of existing investors, we are able to conclude that the observed non-linearity in the performance-flow relation comes from new investors.

Second, from the fund perspective, it is relevant whether the overall lack of sensitivity of net flows to poor performance is simply due to the absence of both inflows and outflows or, instead, to inflows and outflows offsetting one another. Prior research suggests that inflows and outflows are detrimental to fund performance. For example, Chalmers, Edelen, and Kadlec (1999) find that trading in and out of funds increases fund trading costs (commissions and spreads)—leading to lower fund returns. Additionally, Edelen (1999) finds that when trading in and out of funds forces mutual fund managers to trade portfolio securities, they generate lower returns than when they have discretion over the timing of their trades.

Beyond finding that investors respond to both bad and good performance, we also provide evidence on the relative magnitudes of the responses. We argue that in trying to draw inferences about the magnitude of investor responses to performance it is important to hold constant those responding to the performance. While both current and potential investors can purchase fund shares only current investors can sell fund shares. Thus, in gauging the relative magnitudes of investor response to good and bad performance we focus on outflow responses, as these can only come from existing investors. We find that existing investors react to both good and bad performance (by adjusting their outflows) with equal vigor. This result is important because it suggests that, contrary to conjectures in the extant literature, *current* investors respond symmetrically to performance.

Finally, we identify the important roles played by flow persistence and flows in the opposite direction in affecting inferences with respect to the relation between performance and flows. Prior research deals with persistence largely in passing and tends to ignore the potential effects of flows in the opposite direction on inferences with respect to the response of investors to poor performance.[6] We show that including these effects is essential to gaining a full understanding of the relation between performance and flows.

The rest of the paper proceeds as follows. In section 1 we provide a review or the related literature. Section 2 describes the data. Section 3 provides baseline evidence on the relation between performance and flows; it also describes the need to control for flow persistence and flows in the opposite direction. Section 4 analyzes the symmetry (or, lack thereof) of investors' reactions to fund performance, extends the analysis to alternative data periodicity and performance measurement windows, and presents several methodological robustness checks. Section 5 discusses the implications of our results for academics and practitioners and Section 6 concludes.

1. Research Background

1.1 Theoretical Explanations for the Non-linear Response

As noted earlier, there are two broad explanations for the non-linear relation between performance and net flows. The first motivates non-linearity by arguing that existing investors do not respond to poor performance. For example, Gruber (1996) suggests that there are two clienteles of mutual fund investors—sophisticated investors and disadvantaged investors. Disadvantaged investors fail to respond to poor performance because either they are influenced by factors other than return (such as advertising or advice from brokers) or they face some sort of friction that makes response costly. The heterogeneity in existing investors produces an

[6] Cashman, Deli, Nardari, and Villupuram (2006) do consider the role of persistence in monthly mutual fund flows. O'Neal (2004) considers the relation between inflows and outflows at the yearly time interval.

asymmetric response to fund performance.[7]

Rather than relying on investor heterogeneity, Lynch and Musto (2003) suggest that investors rationally choose not to respond to poor performance. They argue that investors believe that following poor performance fund sponsors will either change the portfolio management strategy and/or the management team. Because the investors expect the fund sponsor to change either the management strategy and/or the management team investors have no reason to believe that the poor performance will persist. Thus, current investors rationally choose not to respond to poor performance.

Ivkovic and Weisbenner (2006) introduce the possibility that inactivity by existing investors could be a manifestation of a more general behavioral bias—the disposition effect [Kahneman and Tversky (1979), Shefrin and Statman (1985)]. Specifically, investors may have an aversion to realizing losses which leads to investor inactivity in the face of bad performance. Thus, the disposition effect could explain the hypothesized inactivity of investors in the face of bad performance.

The alternative framework focuses on new investors entering the fund in response to good performance, as opposed to current investors not leaving following poor performance. Huang, Wei, and Yan (2007) make the novel argument that asymmetry in the performance-flow relation is not due to the lack of reaction of existing investors to poor performance, but rather, to differences in participation costs for new investors. They argue that more investors that are new

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[7] Berk and Tonks (2007), in explaining persistence in poor fund performance, also embrace the assumption of heterogeneity in existing investor sensitivity to poor performance. Their basic argument is that investors differ in their sensitivities to poor fund performance. When low-skill managers produce inferior performance current investors with high sensitivities to poor performance exit the fund, leaving behind existing investors who are largely insensitive to poor performance. When the low-quality manager produces inferior performance again in the future there is no response from existing investors because non-responsive, investors. Berk and Tonks (2007) argue that because investors fail to remove assets from poorly performing funds (and thereby moving them towards the smaller optimal fund size) poor performance is able to persist.

to the fund are able to overcome their participation costs as performance increases. This, in turn, leads to a greater sensitivity to performance as fund performance improves.

1.2 Empirical Examinations

As noted in the Introduction, Bergstesser and Poterba (2002), Johnson (2005), and Ivkovic and Weisbenner (2006) find little evidence of a relation between poor performance and outflows. It is important to realize, however, that each of these studies differs from ours in important ways. For instance, Bergstesser and Poterba (2002), Johnson (2005), and Ivkovic and Weisbenner (2006) estimate linear relations (rather than piece-wise linear) between performance and outflows. Also, the samples used in these studies are quite different from ours. For example, Bergstresser and Poterba (2002) use a much smaller sample (686 fund-performance period observations versus our 103,631) while Johnson (2005) and Ivkovic and Weisbenner (2006) use account-level data. Christoffersen, Evans, and Musto (2005) argue that these account level data contain limited, non-random samples of investors and funds. Additionally, they argue that because these data end in the late 1990s, they do not represent investor decisions across different market conditions. Further, Bergstresser and Poterba (2002) do not control for persistence in fund outflows.[8] Recent research by Cashman, Deli, Nardari, and Villupuram (2006) shows that failing to control for persistence in fund flows is likely to lead to incorrect inferences with respect to the relation between performance and flows. Finally, in examining outflows Bergstresser and Poterba (2002) and Ivkovic and Weisbenner (2006) do not control for concurrent inflows.[9] We demonstrate that controlling for concurrent inflows is critical to drawing

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[8] Ivkovic and Weisbenner (2006) do not control for persistence in fund outflows, but they explicitly exclude instances of multiple purchases and multiple sales (by a given investor) from their sample so persistence is not possible in their sample.

[9] Johnson (2005) does not include concurrent inflows in his analysis of outflows, but estimates the relations between

correct inferences with respect to the relation between performance and outflows.[10,11]

While our paper is related to those above, it likely has the most in common with O'Neal (2004). O'Neal (2004) uses annual inflows and outflows to examine investor decisions as a function of fund performance. He concludes that his results "document that investors punish poor performance with increased redemptions, a point questioned in the previous studies of net flows." Oddly though, if punishing poor performance is defined as increased outflows in response to bad performance, O'Neal (2004) finds no evidence that investors actually punish poor performance. What O'Neal (2004) does find is that outflows for funds with average and above average performance tend to decrease as performance increases (for certain measures of performance) with the negative relation being most pronounced for the best performing funds (see his Table III). He finds no relation between performance and outflows among those funds with the worst performance. Thus, O'Neal's results are more appropriately characterized as evidence that investors reward good performance by reducing outflows rather than investors punishing bad performance by increasing outflows. Other issues in O'Neal's analysis, however, lead us to be somewhat skeptical of even that conclusion. For example, O'Neal's results for outflows on the best performing funds are sensitive to his use of market-adjusted returns as his measure of performance. When he uses risk-adjusted returns he finds no relation between performance and outflows (again, see his Table III). Finally, O'Neal's results appear to be sensitive to how he calculates flows. His primary analysis calculates flows as the number of shares traded in a year (purchased, sold, or net) divided by the number of shares at the beginning

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performance and inflows and outflows in a Seemingly Unrelated Regression (SUR) framework.

[10] O'Neal (2004) makes a similar point.

[11] Christoffersen, Evans, and Musto (2005) use gross flows to examine the effects of distribution channel on the performance-flow relation. They use a sample similar to ours, but they do not control for either the persistence in outflows or concurrent inflows.

of a year.[12] When he uses a more traditional measure of flows (albeit with a different sample) based on dollar amounts traded and average assets during the measurement period (and using market-adjusted returns as his measure of performance) he only finds a relation between performance and outflows for funds with average performance (see his Table IX). Again, there is no evidence that bad performance is punished in any way. Also, even O'Neal's result for funds with average performance goes away when he uses risk-adjusted returns as his measure of performance.

2. Data

The sample was compiled using investment companies' N-SAR filings with the SEC, and the Center for Research in Security Prices Survivor Bias Free Mutual Fund Data base (hereafter referred to as CRSP). The SEC requires that all regulated investment companies file two N-SARs each fiscal year, the N-SARA covers the first six months of the investment company's fiscal year, and the N-SARB covers the full fiscal year. We pull all N-SARs from the SEC web site for the calendar years 1997 through 2003. Each N-SAR filing contains the monthly dollar flows in and out of the mutual fund, specifically the N-SAR identifies the dollar amount of purchases, dividend purchases, other purchases, and sold for each month covered by the filing. We define net flows as investor purchases minus investor sales divided by the size of the fund at the beginning of the month (from the N-SAR data).[13] Inflows and outflows are defined similarly. [14]

[12] It is possible that relying on beginning-of-year shares outstanding also creates a relevant bias in O'Neal's results. Relying on beginning of year shares outstanding will overstate percentage outflows for funds that are experiencing growth throughout the year (because the denominator is too small). To the extent this creates a problem, we would expect the problem to be greatest among those funds that had the best performance.

[13] Each N-SAR filing reports the net asset value and the size of the fund at the time of filing (this is always month end) which provides us with the net asset value and the size of the fund at six-month intervals.

[14] Cristoffersen, Evans and Musto (2005) use N-SAR data as well. Deli and Perry (2005) also use gross flow data

We utilize the CRSP database for fund returns, as well as the estimation of abnormal returns, which we define as the realized returns provided by CRSP minus the expected returns. We calculate expected returns using the Fama-French three-factor model plus a momentum factor.[15] Factor loadings are estimated for each fund, every month, based on returns over the prior 36 months. Lastly, CRSP provides us with the Standard and Poors Objective Code, which we use to classify funds into investment categories.

Matching the N-SAR filings with CRSP was not a trivial undertaking. Funds do not have a unique and consistent identifier through time, forcing us to manually compare various fund characteristics to create each fund's time series of N-SAR filings. Once the N-SAR filings were compiled through time, we matched the N-SAR time series to CRSP by manually comparing fund and family names in the two databases. Lastly, to ensure the correctness of our time series match and the match between the two databases, we compare the net asset value reported on the N-SAR filing with that found on CRSP. This provides us with a panel dataset containing 265,750 fund month observations, for the period of April 1997 through June 2003.[16]

We also eliminate from the sample those observations that appear to contain data entry errors. Specifically, we eliminate observations with net flows above the 98th percentile and below the 2nd percentile, inflows above the 96th percentile and below the 4th percentile, and outflows above the 97th percentile and below the 3rd percentile. Doing so results in a loss of 52,112 fund month observations.[17] Next, we ensure that each observation has valid lagged

from the same source, but they use it to examine cross-sectional variation in rapid trading (which they define as inflows matched by outflows within a given month) rather than the relation between performance and subsequent flows.

[15] The Fama French three factors and the momentum factor were downloaded from Kenneth French's web-site: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[16] Our sample starts in 1997 because electronic N-SAR filings were not mandatory prior to 1997.

[17] These cutoffs were determined by the data, each cutoff is set to be the first with a calculated flow value under 50%.

values; this removes 59,042 fund month observations. Lastly, international funds, specialty funds, and hybrid funds are dropped from the sample (61,984 fund months) leaving us with a total of 122,607 fund month observations. Then, we eliminate observations with control variable values indicating data entry error, leaving us with a final sample of 103,631 domestic equity fund month observations.[18]

Table 1 reports descriptive statistics for returns and flows for our sample of domestic equity funds. As might be expected, mean and median raw quarterly returns (equal to 1.5% and 1.6%, respectively) exceed risk adjusted returns which are essentially zero. Perhaps more interesting are the results on fund flows. Average net flows in a month are two percent of fund assets. Average inflows equal 5.4% of fund assets and average outflows equal 3.4% of fund assets.[19] These averages suggest that net flows are small relative to inflows and outflows. This relation is suggested even more strongly by median net flows, inflows, and outflows. Median net flows equal 0.4% of funds assets while the comparable numbers for inflows and outflows are 2.8% and 2.3%, respectively. In other words, median net flows are approximately 1/7th and 1/6th the size of median inflows and outflows, respectively.

3. Empirical Results

3.1 Unconditional analysis

Our first step is to examine whether the performance-net flow relation at the monthly frequency exhibits the same non-linearity documented by previous research at the annual level. As a preliminary examination of the question, we repeat the analysis of Figure 1 from Sirri and

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[18] We drop observations with an effective expense ratio, a redemption fee, or a 12b-1 fee above 2%, or an effective front end load, or deferred sales fee above 7%.

[19] Johnson (2005) finds mean daily inflows and outflows of 0.375% and 0.273%, respectively. Assuming 22 trading days per month suggests mean monthly inflows and outflows of 8.25% and 6.01%, respectively. Thus, Johnson's daily flows appear to suggest monthly trading volumes somewhat higher that those in our sample. The relatively

Tufano (1998). In other words, we take quarterly excess returns and put them into twenty "buckets" from lowest to highest return. We then calculate the average net flow during the next month for the set of observations in each bucket. Results are shown in Figure 1. The results of this simple unconditional analysis are consistent with monthly mutual fund flows exhibiting a non-linear relation to performance. The approximate slope of the relation over the first ten buckets appears to be lower than the slope over the last ten. Additionally, mean net flow jumps dramatically in the buckets with the highest returns.[20]

We next turn our attention to fund outflows. Again, we construct twenty return buckets and then examine mean outflows within each bucket. We find that investors leave funds that perform poorly. The extant literature, which has largely drawn inferences on outflows from results based on net flows, holds that investors do not respond to poor fund performance. Our unconditional results suggest that current investors do respond to poor performance by removing money from poorly performing funds. Finally, Figure 1 also shows that investors leave funds with good performance as well.[21] This result is somewhat surprising and, perhaps, counterintuitive. We consider it further below.

The results for inflows, shown in Figure 1, are also somewhat surprising. Consistent with our expectations, good performance results in inflows to the fund in the next month. Unexpectedly, however, the same appears to be true for bad performance (at least relative to the inflows for more moderate levels of performance). In other words, investors appear to respond to

small sample (less than ten funds) in Johnson's analysis may account for the difference.

[20] The average monthly flow following performance in the top bucket is slightly over 3.8% of fund assets. On an annual basis that would approximately imply a net inflow equal to 46% of fund assets. That amount is consistent with the findings of Sirri and Tufano (1998).

[21] Christofersen, Evans, and Musto (2005) document a similar result in their unconditional analysis. In his unconditional analysis of outflows, O'Neal (2004) finds that outflows are greater for funds with the best performance, and the same for all other funds across the performance spectrum (including funds with poor performance).

both good and bad performance with increased inflows. The relation does appear, however, to be much stronger for good performance.

3.2 Multivariate Analysis

To conduct a more formal evaluation of the non-linearity in monthly flows we examine the performance-flow relation in a regression framework. Following Sirri and Tufano (1998) we measure performance using fractile rankings. Each month we rank funds based on their prior quarter performance, ranging from 0 for the worst performing fund to 1 for the best performing fund. We divide performance fractile rankings into terciles and estimate a piecewise linear regression.[22] As our primary estimation and inference methodology we use the Fama and MacBeth (1973) approach to estimate such non-linear regressions. We compute robust standard errors using the method of Newey and West (1987) with four lags.[23] In addition, we also estimate the regression using Pooled OLS. Given the strong possibility of residual correlation both across time and across funds, we calculate clustered (or, Rogers) standard errors where the clustering is done either by time or by fund.[24]

Sirri and Tufano (1998) find that annual net flows are negatively related to fund expenses. This suggests that we should control for a fund’s expense ratio when examining monthly fund flows. They also find that 12b-1 fees affect fund flows. Therefore, we control for the level of 12b-1 fees as well. Nanda, Wang, and Zheng (2003) find that cash flow volatility increases with the introduction of multiple fund share classes. Therefore, we use an indicator variable to capture whether a fund has multiple share classes. Chevalier and Ellison (1997) and Huang, Wei, and

[22] To make sure our results are not driven by setting our breakpoints at the 33rd and 67th percentiles of performance, we also try several other breakpoint specifications. (e.g., 20-60-20, 10-80-10) and find similar results.
[23] Using 1,2 or 3 lags does not alter our inferences. See Huang, Wei and Yan (2007) for a similar treatment.
[24] In most of our experiments, clustering errors to account for cross-sectional residual correlation yields more conservative (i.e, larger) standard errors than clustering to allow for serial correlations among each fund's residuals. We, therefore, report in our tables t-statistics based on the former.

Yan (2007) argue that fund age potentially affects the performance-flow relation so we include the natural log of one plus fund age in the regressions. Finally, Sirri and Tufano (1998) suggest that it is appropriate to control for total fund risk when examining fund flows so we control for the level of fund risk with the standard deviation of monthly (abnormal) returns for each fund.

We also control for trading fees. We do so because it seems likely that frictions associated with trading may affect the level of trading. Rather than using an indicator variable capturing the presence of a fee (front-end loads, contingent deferred sales charges, and redemption fees), we compute effective measures for each type of trading fee. N-SAR data provide us with the dollar amount of each type of trading fee collected over each six-month reporting period.[25] To derive our measures of effective fees, we divide the total amount of a fee collected over a period by the total amount of trading that could possibly have been subject to that fee. For example, to calculate our measure of effective front-end loads we divide the amount of front-end load fees by the total amount of inflows during the six-month reporting period.[26] Using this methodology, we calculate effective front-end loads, effective back-end loads, and effective redemption fees.

We examine the determinants of monthly net flows in Table 2. The results suggest that the monthly performance-net flow relation is, in fact, non-linear. For example, in the Fama-MacBeth estimation, the slope between performance and net flows is positive over the tercile of the worst performing mutual funds, becomes weakly negative over the middle tercile, and turns positive again for performance in the top tercile. The positive coefficient for funds in the highest tercile of performance is approximately two and a half to three times as large as the coefficient for funds in the bottom tercile. In combination with the results reported in Figure 1, we take these results as confirming that the monthly performance-flow relation is non-linear.

[25] Unfortunately, N-SAR data do not contain fees collected on a monthly basis.

Finding a non-linear relation between quarterly performance and monthly net flows is important for two reasons. First, it suggests that at least some investors evaluate mutual fund performance more frequently than on an annual basis [Cashman, Deli, Nardari, Villupuram (2006)]. If all investors evaluate and respond to performance over longer windows then we would not expect any systematic relation between quarterly performance and net flows (or, for that matter, between quarterly performance and gross flows). Second, it indicates that the "shape" of the net flow response at the monthly time interval is similar to that observed for annual flows with respect to annual performance. This, in turn, suggests that our results on the quarterly performance-monthly flow relation are likely to generalize to longer performance evaluation and response windows.[27] Overall, we take the similarity of our results to prior results that use longer windows to suggest that monthly flows are a reasonable context for examining investor responses to fund performance. In addition, the substantially larger number of observations at our disposal makes for a non-trivial increase in the statistical power of our analysis when compared to those based on annual flows.

We next turn our attention to fund outflows. We examine outflows in Table 3. Given the results shown in Figure 1, our expectation is that outflows will exhibit a U-shaped relation to performance. In the first specification of Table 3, we see that the slope of the relation between performance and outflows is significantly negative over the worst performance tercile, less negative though still statistically significant over the middle performance tercile and is significantly positive over the best performance tercile. This result is similar to that found by Christoffersen, Evans, and Mutso (2005).[28] The negative coefficient on the relation between

[26] Thus, a particular fund will have the same values for effective fees for six consecutive monthly observations.
[27] Although our baseline results are obtained from monthly data, we do conduct robustness checks at quarterly horizons. These are discussed in Section 4.2.
[28] We will discuss the similarity of our base results, along with how subsequent results differ, in section 3.3.

performance and outflows for those funds with the lowest returns suggests that investors withdraw more money from poorly performing funds. This result stands in stark contrast to the conventional wisdom that investors do not respond to poor performance.

Cashman, Deli, Nardari, and Villupuram (2006) find that monthly net flows, outflows, and inflows are all highly persistent. They also find that persistence has a meaningful effect on the inferences one draws with respect to the relation between performance and flows. Their results suggest that it is important that we control for the persistence of flows in our multivariate analysis. We see from the results of specification (2) that our inferences are, indeed, sensitive to the omission of lagged outflows from the analysis. In specification (2), where we control for the persistence in fund outflows, we see that the relation between performance and outflows for funds in the top tercile of performance becomes statistically insignificant (though still positive). Overall, we take the results of Table 3 to suggest that current investors do punish funds for poor performance by withdrawing more money from those poorly performing funds.

We next repeat our analysis for fund inflows. Again, given the results shown in Figure 1, our expectation is that inflows will demonstrate a positive response to good fund performance. We show that is indeed the case in Table 4. The slope of the relation between performance and inflows is significantly positive over the highest tercile of return outcomes. In other words, investors put more money into funds with strong performance. This result is consistent with the inferences drawn from studies of annual net fund flows.

To summarize, our initial results are as follows. Contrary to the inferences of prior research, current investors do appear to punish poorly performing mutual funds by withdrawing money from those funds. We also confirm that current and potential investors respond to strong performance by increasing their purchases of funds with good performance. There remain two questions, however. First, why don't current and potential investors respond to poor performance by reducing inflows? Recall that our analysis indicates that the only response to poor performance comes through increased outflows. Similarly, why don't current investors respond to good performance by reducing their withdrawals of money from those funds that perform well? We now turn our attention to answering those questions.

3.3 Controlling for Flows in the Opposite Direction

It seems possible that at least some portion of trading in one direction (for example outflows) is explained by trading in the other direction. For example, O'Neal (2004) argues that there is a relevant fraction of mutual fund investors that, for whatever reason, move in and out of funds over a relatively short time period. He finds this to be the case for annual flows. Additionally, recent research suggests that traders moving quickly in and out of mutual funds may have a meaningful effect on observed patterns in mutual fund flows [Chalmers, Edelen and Kadlec (2001), Greene and Hodges (2002), and Zitzewitz (2003)].[29] It seems reasonable to suggest, then, that controlling for contemporaneous trade in the opposite direction is important to our inferences with respect to the relation between performance and flows. Accordingly, we examine the relations between performance and both outflows and inflows, while controlling for flows in the opposite direction. For example, when examining outflows in the first two regression specifications of Table 5 we include contemporaneous inflows. Likewise, when we examine inflows in the final two regression specifications of Table 5 we include contemporaneous outflows.

We first turn our attention to the relation between performance and outflows. Remember

[29] Chalmers, Edelen and Kadlec (2001), Greene and Hodges (2002), and Zitzewitz (2003) use daily flow data from TrimTabs to demonstrate the ability of these traders to systematically transfer wealth from long-term investors to themselves. The TrimTabs data capture flows for a small subset of mutual funds (about 12% of U.S. open-end funds [Zitzewitz (2003)]) over a relatively brief period of time [for example, Zitzewitz's (2003) sample, covers

that in earlier analysis we only establish a negative relation between performance and outflows for funds in the worst performance tercile. When we control for flows in the opposite direction the negative relation between performance and outflows for funds in the worst performance tercile remains, but the relation between performance and outflows for the best performing funds is negative as well. This result suggests that not only do current investors punish poorly performing funds by increasing their withdrawals, but current investors also reward funds with strong performance by reducing their withdrawals from those funds.

In our previous analysis it was also somewhat enigmatic that, while current and potential investors appear to reward good performance with increased inflows, current and potential investors do not punish bad performance by reducing their purchases of fund shares. We see that once we control for flows in the opposite direction, our inference changes. We see in the final two regression specifications of Table 5 that for funds in the bottom tercile of fund performance there is a positive relation between performance and inflows. In other words, among the worst performing funds, funds that do worse are punished by existing and potential investors who reduce their purchases of fund shares.

Our results in this section highlight the importance of controlling for factors other than performance when examining the relation between performance and flows. We reexamine the point graphically in Figure 2. For the analysis in Figure 2, we use coefficient estimates from the Fama-MacBeth analysis to map the relation between performance and fund flows (setting non-performance measures to their means). For example, in panel A1 of Figure 2 we use the coefficient estimates from specification (1) of Table 3. We set each of the control variables equal to its mean, vary the performance quantile from zero to one, and then plot the implied outflows.

January 1998 to October 2001].

Panel A2 presents the implied outflows using specification (2) from Table 3 (i.e., including lagged inflows). Panel A3 presents the implied outflows while controlling for both lagged outflows and contemporaneous inflows. Panels B1-B3 present a similar analysis for inflows.

Panels A1-A3 show the importance of controlling for the persistence in outflows and flows in the opposite direction when examining the relation between performance and outflows. When we fail to control for flow persistence and flows in the opposite direction in panel A1 we see the U-shaped relation between performance and outflows discussed earlier. Failing to control for persistence and flows in the opposite direction would lead to an erroneous inference with respect to the relation between performance and outflows for funds that performed particularly well. Specifically, it would lead to the belief that current investors withdraw assets from better performing funds. Controlling for flow persistence suggests relative indifference to good performance on the part of current investors (panel A2). Even that conclusion is called into question, however, when we control for flows in the opposite direction. When we control for flows in the opposite direction in panel A3 we see that current investors actually reward good performance by reducing their withdrawals from the fund.

This point motivates a comparison of our results with those of Christoffersen, Evans, and Musto (2005). Christoffersen, Evans, and Musto (2005) do not control for persistence in fund outflows or for inflows when they examine the relation between performance and outflows. They find a relation similar to Figure 2, panel A1—namely that outflows are negatively related to performance for the worst performing funds, unrelated to performance for funds with average performance, and positively related to performance for the best performing funds (see their Table 4). These results lead to the somewhat internally inconsistent conclusion that investors rebalance out of winners (to restore diversification), but abandon the worst performers (rather than increasing their investment to restore diversification). Our results depicted in panels A1-A3 in Figure 2, suggest that their results on the shape of the performance-outflow relation would probably be meaningfully different were they to control for outflow persistence and inflows.[30]

Panels B1-B3 show that our inferences with respect to the relation between performance and inflows for poorly performing funds changes in a similar fashion. When we fail to control for flow persistence and outflows it appears that, at least to some extent, current and potential investors are indifferent to poor performance. When we control for persistence and flows in the opposite direction, however, we see that investors punish poor performance by reducing their purchases of fund shares. Overall, the results depicted in Figure 2 emphasize the importance of controlling for non-performance influences on flows when examining the relation between performance and subsequent flows.

4. Additional Analysis

In this section, we first discuss the relative magnitudes of investor responses to good and bad performance. Specifically, we offer evidence that *current* investor response to performance is symmetric, contrary to what is typically argued by the extant literature. We then provide evidence on investor reactions to fund performance at different time intervals. Finally, we present additional robustness checks for the econometric methodology.

4.1 Is Investor Response to Performance Asymmetric?

It has long been held that investor response to performance is asymmetric—investors reward good performance and are indifferent to bad performance. As noted earlier, that belief is

[30] It is important to realize that the focus of the relevant portions of Christoffersen, Evans, and Musto (2005) is on how distribution channels affect the performance-flow relation. That is, they are examining the incremental effect of one distribution channel relative to another. It is not obvious that any of their results on that dimension would be affected in any meaningful way were they to control for outflow persistence or inflows.

based on the oft-documented non-linear relation between performance and *net* flows. By examining gross flows we are able to document that: (1) bad performance is punished by current investors increasing their outflows and current and potential investors decreasing their purchases of fund shares, and (2) good performance is rewarded by current and potential investors buying more fund shares and current investors reducing the amount of money they withdraw from the fund.

It is important to note the distinction we make between exactly who is able to respond to fund performance.[31] Only investors who are currently in a fund have the ability to withdraw money while both current and potential investors (i.e., those who are not currently in the fund) have the ability to purchase fund shares. Ideally, in gauging investor response to performance we would like to hold the investor (i.e., responding) group constant.

The only performance-flow relation over which we are able to hold the responding group constant is the relation between performance and outflows. Inflows involve a possibly changing mix of current and potential investors. When we control for the persistence in outflows and for flows in the opposite direction in panel A3 of Figure 2, we see that the response of current investors to bad performance is the same as it is to good performance. That is, current investors punish bad performance by increasing withdrawals with the same vigor that they reward good performance by reducing outflows. This fact is confirmed empirically by comparing the relevant regression coefficients from Table 5. A Wald test of equality of the two coefficients (-0.007 and -0.006) is computed by using the coefficient covariance matrix provided by the Fama-MacBeth procedure.[32] The (chi-squared) test is unable to reject the null of equality. Additionally, we compare the mean coefficients for the worst and best performance terciles from our 75 cross

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[31] This point is also made by Berk and Tonks (2007).

sectional regressions. This difference in means test is also unable to reject the null hypothesis that the coefficients are equal. Lastly, we compare the worst and best performance terciles coefficients estimates using an F-test from our pooled OLS analysis: once more, we find that the difference in the coefficients is statistically insignificant. Our results, then, suggest that, when we are able to hold the investor group constant, we find evidence that current investors respond with equal intensity (on outflows) to both bad and good performance. This result stands in sharp contrast to the conventional wisdom of asymmetric investor responses to fund performance.

4.2 Evidence from Other Performance and Flow Windows

One potential concern about our results is that they may not be generally descriptive. For example, there may exist different clienteles of investors with respect to the periodicity over which they evaluate and respond to fund performance. Our results may only be descriptive for investors who evaluate and respond to performance over a specific period of time (i.e., quarters). However, we suspect that this is not an issue because the relation we observe between quarterly performance and net flows is consistent with that observed for annual performance and net flows. First, we repeat all of our analysis using semi-annual and annual performance (rather than quarterly performance). For brevity, we leave the results untabulated, but show them graphically in Figure 3. Figure 3 shows the relation between outflows and performance as well as the relation between inflows and performance while controlling for lagged flows and cross flows. The relations depicted in Figure 3 are similar to those shown in Figure 2. Even at longer performance evaluation windows, investors punish bad performance by increasing outflows (and decreasing inflows) and reward good performance by reducing outflows (and increasing inflows). Thus, we conclude that our results are not driven by our choice of a quarterly

[32] See Cochrane (2005), Chapter 12, for a reference.

performance evaluation period.

Next, we repeat all of our analysis using quarterly performance and flows instead of monthly performance and flows.[33] We report our quarterly outflow and inflow results in Figure 4 and Table 6. The results mirror those from our monthly analysis. We see a U-shaped relation between performance and outflows when we do not control for persistence in fund outflows (panel A1). When we control for both persistence in flows and contemporaneous cross trading in panels A3 and B3 we see that current investors punish poor performance by withdrawing money and reward good performance by reducing their withdrawals from funds that have done well. Similarly, we see that current and potential investors reward funds for good performance by increasing their purchases of fund shares while at the same time punishing poor performance by reducing their purchases.

Table 6 also shows that the symmetry of response to good and bad performance by existing investors holds at the quarterly interval as well. For example, in the Fama-MacBeth regression results we see that the slope of the relation between performance and outflows for funds in the first tercile of fund performance is -0.023 while the slope of the relation for funds in the highest tercile of fund performance is -0.031. The two coefficients are not statistically different from one another based on a Wald test. In other words, current investors react to poor performance (by increasing their sales of fund shares) with the same vigor they display when they respond to good performance (by reducing their sales of fund shares). Again, this evidence runs contrary to the notion that current investors are essentially indifferent to bad fund performance. As an additional test, we investigate the performance-flow sensitivity using quarterly flows but

[33] We note that in (untabulated) results for quarterly net flows we find the same non-linear relation between performance and net flows that we found for monthly performance (and the same as prior research on the annual performance-flow relation).

regressing them on performance measured over the previous year.[34] All results from this specification are extremely close to what we find previously and thus, are not reported. Overall, our results using quarterly performance and quarterly flows have similar patterns to those using quarterly performance and monthly flows.[35]

4.3 Further Robustness Issues

As an alternative to the Fama-MacBeth and the Pooled OLS methods, one could attempt to exploit more directly the panel features of the data. In particular, if there were unobservable (or, omitted) fund characteristics affecting investments flows, a panel regression with, say, fixed effects could be more appropriate. To accommodate this possibility, we run a fixed effect panel estimation for all our flow regressions. We use a standard Within Estimator and correct the standard errors for general cross-correlation as well as for cross-sectional heteroskedasticity across fund residuals. Alternatively, we correct for general serial correlation in the residuals of each fund.[36] The pattern of magnitudes and significance (or, lack of it) reported in Tables 2 through 6 is essentially unaltered. Consequently, both the ordinal and the cardinal differences presented in the previous sections appear to be very robust to the inclusion of fund fixed effects.

Complications arise in a panel estimation when lagged dependent variables are included among the regressors.[37] Specifically, if the independent variables are not strictly exogenous (as it is the case whenever endogenous regressors are present), the standard fixed-effect estimator is inconsistent. In principle, one would then rely on dynamic panel methods, which typically

[34] These are, respectively, the periodicity and the performance evaluation horizon used by Ivkovic and Weisbenner (2006) when they aggregate individual trades to fund level flows (please, see their section 5).
[35] Unfortunately, our sample period is not long enough to examine the annual performance-flow relation.
[36] Specifically, we compute White standard errors adjusted to account for possible correlation across funds. Petersen (2006), among others, refers to these standard errors as clustered (or, Rogers) standard errors, where the clustering is across funds at a given point in time or, alternatively, across time for each fund.
[37] Comprehensive references to this problem and, more generally, to the econometrics of panel data are Wooldridge (2002) and Baltagi (2001).

employ Generalized Method of Moments (GMM) techniques.[38] Two considerations, however, make them less appealing for our framework. One, an attempt to achieve the efficiency gains induced by GMM would likely be infeasible because of the enormous number of moment conditions the estimation would require. In fact, in such a situation GMM may well generate downward biased estimates.[39] Two, as Wooldridge (Ch. 11) shows, the inconsistency of the fixed effect estimators is of order 1/T, where T denotes the time-series sample size. While in most panel analyses (typically based on annual data) this is a serious concern, in our dataset (T=75) the distortions are likely to be quite small.

In sum, after a battery of checks on the estimation methodology and/or on the inferential approach, we conclude that all our main findings are robust.

5. Implications for Academics and Practitioners

We find evidence that current investors do respond to poor performance. We also find that their response to poor performance is similar in magnitude to their response to good performance. Still, it remains the case that net flows do not appear to respond to poor performance to the same extent that they respond to good performance. At some level, that realization would seem to beg the question of why we care about disaggregating net flows into outflows and inflows?

From an academic perspective our results are important because they shift the focus in current efforts to explain the non-linear performance-flow relation from current investors to investors entering the fund. The conventional wisdom has been that the observed non-linearity in

[38] Some prominent references in this area are Arellano and Bond (1991), Arellano and Bover (1995) or Ahn and Schmidt (1995).

[39] The number of moment conditions is proportional to both the number of exogenous regressors and to the number of time series observations. With a dataset like ours, one is quite likely to face a bias/efficiency trade-off when using

the performance-flow relation is a by-product of existing investors essentially being insensitive to fund performance. Our results suggest that focusing on current investors as an explanation for the non-linear relation between performance and net flows is misguided. Specifically, we find that current investors do respond to fund performance and they respond in a symmetric fashion. This suggests that theoretical work aimed at understanding the non-linear relation between performance and flows should focus its attention on investors who are purchasing fund shares. As noted earlier, this is precisely the tact taken by Huang, Wei, and Yan (2007). Their argument is that the non-linearity in the performance-flow relation is driven by differential participation costs for *new* investors. Although our results do not provide a direct test of their theory, they do suggest, at a minimum, that Huang, Wei, and Yan's (2007) theory is in the correct class of theories (i.e., those focusing on new investors) for explaining the non-linear relation between performance and net flows.

Additionally, Christoffersen, Evans, and Musto (2005) and Ivkovic and Weisbenner (2006) suggest that it is possible that mutual fund outflows can provide evidence on the disposition effect of Kahneman and Tversky (1979) and Shefrin and Statman (1985). As noted earlier, the disposition effect, in short, asserts that individual investors have an aversion to realizing losses (and a propensity to cash in gains). It seems likely that account-level data such as that used by Ivkovic and Weisbenner (2006) is best suited for providing evidence related to individual trading decisions, but to the extent outflows aggregated within a fund are a reasonable representation of individual investor decisions, we note the following. The disposition effect suggests that fund investors should sell those funds with the best performance. We find just the opposite—investors actually reduce their sales of the best-performing funds. The disposition effect also suggests that

dynamic panel methods. See Baltagi, Chapter 8.7 for a thorough discussion of this point.

investors should hold on to the worst performing funds. Again, we find just the opposite—investors tend to increase their sales of the worst performing funds. In sum, our evidence on disaggregated flows is inconsistent with the disposition effect.

While our results are inconsistent with the disposition effect, they do speak to the theory of Berk and Green (2004). Berk and Green (2004) model a world in which investors are assumed to correctly believe that mutual fund managers have persistent skill and update their beliefs about managerial skill based on observed performance outcomes. They combine those assumptions with an assumption of diseconomies of scale and derive an equilibrium where performance is not persistent. Our evidence that investors sell following bad performance and buy in response to good performance is consistent with beliefs in persistent skills. To the extent that providing empirical evidence that is consistent with an underlying assumption of a theory provides support for that theory, it could be argued that our results provide empirical support for the equilibrium model of Berk and Green (2004).

At first blush it might appear that our results on outflows and inflows would be of little interest to mutual fund practitioners. It might be argued that they only care about net flows rather than gross flows. This is unlikely for at least two reasons. First, prior research suggests that inflows and outflows (as opposed to net flows) are detrimental to fund performance. For example, Chalmers, Edelen, and Kadlec (1999) find that trading in and out of funds increases fund trading costs (commissions and spreads)—leading to lower fund returns. Edelen (1999) finds that when trading in and out of funds forces mutual fund managers to trade portfolio securities, they generate lower returns than when they have discretion of the timing of their trades.

Second, identifying the fact that purchasing investors are the source of non-linearity in the performance-net flow relation is also likely to be important to practitioners. To see this, it is important to understand the context in which almost all studies (including this one) on mutual fund flows have been conducted. The mutual fund industry has experienced positive and generally increasing net flows for many years. Net cash flows into equity mutual funds have increased from $7 billion in 1985, to $124 billion in 1995, and to $136 billion in 2005 [Investment Company Institute (2006)]. Our sample exhibits positive net inflows as well with an average (median) net inflow of 2% (0.4%) per month. Although we have no direct evidence, it seems reasonable to assume that at least some portion of these net inflows is explained by evolving demographics. The ICI reports that mutual fund ownership increases with investor age as investors accumulate savings for retirement. The ICI also reports that, "About half of all [mutual fund] shareholders are members of the Baby Boom Generation." It seems plausible that the demographic group of aging Baby Boomers purchasing fund shares for retirement plays an important role in the observed non-linearity in net flows. Identifying the fact that purchasers drive the non-linearity in net flows is important because it seems likely that once the large demographic group of Baby Boomers reach retirement and switch from being net purchasers to net sellers, the relation between performance and net flows will likely change.

6. Conclusion and Future Research

One of the best-documented empirical regularities in mutual fund research is the non-linear relation between past performance and net flows. Typically, the non-linear relation is argued to exist because, while investors reward funds for good performance, they do not punish them for comparable bad performance. To examine if investors reward good performance but fail to punish bad performance we examine the relation between performance and gross flows. We find that investors do reward good performance; however, we also find that existing investors punish poor performance. We also find that current and potential investors punish bad performance by reducing their purchases of fund shares. Finally, we find that the performance-outflow relationship is symmetric. Current investors punish poor performance with the same intensity that they reward good performance.

Our finding that current investors respond symmetrically to performance implies that the asymmetry in the relationship between performance and net flows is driven by asymmetry in the response of new investors to performance. This evidence supports the theoretical framework of Huang, Wei, and Yan (2007), which focuses on the response of new investors to performance to explain the asymmetric performance flow response.

REFERENCES

Ahn, Seung and Peter Schmidt, 1995, Efficient estimation of models for dynamic panel data. *Journal of Econometrics* 68, 5–28.

Arellano, Manuel and Stephen R. Bond, 1991, Some tests of specification for panel data: Monte-Carlo evidence and an application to employment equations, *Review of Economic Studies* 38, 277–297.

Arellano, Manuel and Olympia Bover, 1995, Another look at instrumental-variable estimation of error-components models, *Journal of Econometrics* 68, 29–52.

Baltagi, Badi H., 2001, Econometric Analysis of Panel Data, John Wiley and Sons, New York.

Bergstresser, Daniel and James Poterba, 2002, Do after-tax returns affect mutual fund inflows?, *Journal of Financial Economics* 63, 381-414.

Berk, Jonathan B., and Ian Tonks, 2007, Return Persistence and Fund Flows in the Worst Performing Mutual Funds, working paper, National Bureau of Economic Research.

Bhargava R. and D. A. Dubofsky, 2001, A Note on Fair Value Pricing of Mutual Funds, *Journal of Banking and Finance* 25, 339-354.

Cashman, George D., Daniel N. Deli, Federico Nardari and Sriram V. Villupuram, 2006, On Monthly Mutual Fund Flows, working paper, Arizona State University.

Chalmers, John M. R, Roger M. Edelen and Gregory B. Kadlec, 1999, An Analysis of Mutual Fund Trading Costs, working paper, University of Oregon.

Chalmers, John M. R, Roger M. Edelen and Gregory B. Kadlec, 2001, On the perils of Financial Intermediaries Setting Securities Prices: The Mutual Fund Wild Card Option, *The Journal of Finance* 56, 2209-2236.

Chevalier, Judith and Glenn Ellison, 1997, Risk Taking by Mutual Funds as a Response to Incentives, *Journal of Political Economy* 105, 1167-1200.

Christoffersen, Susan, Richard Evans and David Musto, 2005, The Economics of Mutual-Fund Brokerage: Evidence from the Cross Section of Investment Channels, University of Pennsylvania working paper.

Cochrane, John H., 2005, Asset Pricing, Princeton University Press, New Jersey.

Del Guercio, Diane and Paula A. Tkac, 2002, The determinants of the flow of funds of managed portfolios: Mutual funds vs. pension funds, *Journal of Financial and Quantitative Analysis* 37, 523-557.

Deli, Daniel N. and Tod Perry, 2005, On Rapid Trading in Mutual Fund Shares, working paper, Arizona State University.

Edelen, Roger M., 1999, Investor Flows and the Assessed Performance of Open-end Mutual Funds, *Journal of Financial Economics* 53, 439-466.

Fama, Eugene F. and James D. MacBeth, 1973, Risk, Return and Equilibrium: Empirical Tests, *The Journal of Political Economy* 81, 607-636.

Goetzmann, William N., Zoran Ivkovic and K. Geert Rouwenhorst, 2001, Day Trading International Mutual Funds, *Journal of Financial and Quantitative Analysis* 36, 287-309.

Greene, Jason. and C. Hodges, 2002, The dilution impact of daily fund flows on open-end mutual funds, *Journal of Financial Economics* 65, 131-158.

Gruber, Martin J., 1996, Another puzzle: The growth in actively managed mutual funds, *Journal of Finance* 51, 783-810.

Huang, Jennifer, Kelsey D. Wei and Hong Yan, 2007, Participation Costs and the Sensitivity of Fund Flows to Past Performance. *Journal of Finance* 62, 1273-1311.

Ippolito, Richard A., 1992, Consumer reaction to measures of poor quality: Evidence from the mutual fund industry, *Journal of Law and Economics* 35, 45-70.

Investment Company Institute, 2006, Fact Book, Investment Company Institute, Washington, D.C.

Ivkovic, Zoran and Scott Weisbenner, 2006, “Old” Money Matters: The sensitivity of Mutual Fund Redemption Decisions to Past Performance, working paper, University of Illinois

Johnson, Woodrow T., 2005, Who monitors the mutual fund manager, new or old shareholders?, working paper, University of Oregon.

Kahneman, Daniel and Amos Tversky, 1979, Prospect theory: An analysis of decision under risk, *Econometrica* 47, 263-291.

Lynch, Anthony W. and David K. Musto, 2003, How Investors Interpret Past Fund Returns, Journal of Finance 58, 2033-2058

Nanda, Virkam, Z. Jay Wang, and Lu Zheng, 2003, The ABCs of mutual funds: A natural experiment on fund flows and performance, working paper, University of Michigan.

Newey, Whitney, and Kenneth West, 1987, A Simple, Positive Semi-Definite, Heteroscedastic and Autocorrelation Consistent Covariance Matrix, *Econometrica* 55, 703-708.

O’Neal, Edward, 2004, Purchase and redemption patterns of US Equity mutual funds, *Financial*

Management, Spring 2004, 63-90.

Petersen, Mitchell A., 2006, Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches, working paper, Northwestern University.

Shefrin, Hersh M. and Meir Statman, 1985, The disposition to sell winners too early and ride losers too long: Theory and evidence, *Journal of Finance* 40, 777-792.

Sirri, Erik R. and Peter Tufano, 1998, Costly Search and Mutual Fund Flows, *Journal of Finance* 53, 1589-1622.

Wooldridge, Jeffrey, 2002, Econometric Analysis of Cross Section and Panel Data, MIT Press, Cambridge, MA.

Zitzewitz, Eric, 2003, How Widespread is Late Trading in Mutual Funds?, working paper, Stanford University.

Table 1. Descriptive Statistics for Domestic Equity Funds. The sample consists of 2,619 domestic equity mutual funds from a combination between the CRSP Survivor-Bias-Free US Mutual Fund Database and N-SAR filings with the SEC. There are 103,631 fund month observations for the period April 1997 to June 2003. Panel A presents the descriptive statistics of the fund's monthly raw and abnormal returns, where abnormal return is the fund's Carhart four factor adjusted return. The risk adjustment is done using a rolling beta estimate over the prior 36 months. Panel B presents descriptive statistics for the fund's monthly net flow, and component flows. *Net Flows* is the amount of new money invested with the fund minus the amount of money withdrawn from the fund during a month, divided by the fund's total net assets at the beginning of the month. *Inflow* is the amount of new money invested into a fund over the month, divided by the fund's total net assets at the beginning of the month. *Outflow* is the amount of money withdrawn from the fund over the month, divided by the fund's total net assets at the beginning of the month. All figures are in decimal form (e.g., .03 equals three percent).

Panel A. Descriptive Statistics for Raw and Abnormal Returns

	Mean	Median	Maximum	75^{th} Percentile	25^{th} Percentile	Minimum	Std. Dev.
Raw Returns	0.015	0.016	1.172	0.087	-0.061	-0.650	0.133
Abnormal Returns	-0.003	-0.005	0.887	0.021	-0.033	-0.881	0.061

Panel B. Descriptive Statistics for Net Flows Inflows and Outflows

	Mean	Median	Maximum	75^{th} Percentile	25^{th} Percentile	Minimum	Std. Dev.
Net Flows	0.020	0.004	0.426	0.029	0.008	-0.116	0.060
Inflow	0.054	0.028	0.477	0.065	0.013	0.001	0.068
Outflow	0.034	0.023	0.395	0.040	0.013	0	0.037

Table 2. Net Flows to Domestic Equity Funds. This table presents results from Fama-MacBeth and Pooled OLS regressions on our sample of 2,619 domestic equity mutual funds. There are 103,631 fund month observations from April 1997 to June 2003. The dependent variable is *net flow*, which is the amount of new money invested in the fund minus the amount of money withdrawn from the fund over a month, divided by the size of the fund at the beginning of the month. The independent variables are *Performance Terciles*, where performance is the fractile ranking of Carhart four factor adjusted quarterly return (where the adjustment is based on rolling betas estimates over the prior 36 months). *Lagged NetFlows* represent lags 1 through 12 of the dependent variable. *LnAge* is the natural log of the number of months that the fund is in the CRSP database. *Multiclass* is an indicator variable that takes the value of one if the fund offers more than one share class, and is zero otherwise. *LnSize* is the natural log of the fund's total net asset at the beginning of the month. *StdRet* is the standard deviation of the fund's abnormal monthly returns over the previous 12 months. *ExpenseRatio* is the expense ratio over the six month N-SAR reporting period. *EffectiveFrontLoad* is the money that the fund collected from the front-end load over the six month reporting period divided by the amount of new money flowing into the fund over the same six month reporting period. *EffectiveRedemptionFee* is the money generated from the fund's redemption fee over the six month reporting period divided by the amount of money withdrawn from the fund during the same six month reporting period. *EffectiveCDSC* is the money collected from the fund's contingent deferred sales charges over the six month reporting period divided by the amount of money withdrawn from the fund during the same six month reporting period. *12b-1 Fee* is the money generated for the fund from 12-b1 fees over the six month reporting period divided by the size of the fund at the time of the N-SAR filing. t-statistics are in parentheses. Significance is based on Newey-West standard errors in Fama-MacBeth regressions and Rogers standard errors clustered by time in Pooled OLS regressions. ** indicates significance at the 1% level. * indicates significance at the 5% level.

	Fama/MacBeth		Pooled OLS	
	(1)	(2)	(3)	(4)
Intercept	0.073**	0.018**	0.073**	0.021**
	(25.50)	(8.52)	(20.30)	(6.46)
Worst Performance Tercile	0.021**	0.009**	0.021**	0.010**
	(6.31)	(4.06)	(5.74)	(3.55)
Middle Performance Tercile	0.0002	0.003	-0.001	0.004*
	(0.08)	(1.98)	(-0.30)	(2.35)
Best Performance Tercile	0.054**	0.028**	0.057**	0.032**
	(13.00)	(10.10)	(9.58)	(7.20)
LnAge	-0.006**	-0.0002	-0.007**	-0.0003
	(-13.70)	(-0.79)	(-14.90)	(-0.74)
Multiclass	0.001	0.0003	0.000	30.001
	(1.74)	(0.68)	(0.50)	(1.13)
lnSize	-0.002**	-0.001**	-0.002**	-0.001**
	(-17.20)	(-10.10)	(-13.30)	(-9.05)
StdRet	0.122	0.295	0.232	-0.024
	(0.47)	(1.30)	(0.76)	(-0.08)
ExpenseRatio	-2.059**	-0.731**	-2.049**	-0.789**
	(-21.40)	(-12.50)	(-20.60)	(-8.84)
EffectiveFrontLoad	0.211**	0.013	0.255**	0.035
	(7.44)	(0.84)	(8.34)	(1.54)
EffectiveRedemptionFee	2.280**	0.780	1.530**	0.240
	(5.50)	(1.76)	(4.94)	(1.15)
EffectiveCDSC	0.458**	0.116	0.348**	0.126*
	(6.38)	(1.99)	(7.27)	(2.13)
12b-1 Fee	1.183**	0.423**	1.029**	0.303*
	(6.73)	(3.57)	(6.12)	(2.37)
Lagged Net Flows Included?	No	Yes	No	Yes
Adj-R^2	0.09	0.37	0.06	0.26

Table 3. Outflows to Domestic Equity Funds. This table presents results from Fama-MacBeth and Pooled OLS regressions on our sample of 2,619 domestic equity mutual funds. There are 103,631 fund month observations from April 1997 to June 2003. The dependent variable is *outflow*, which is the amount of money withdrawn from the fund over a month, divided by the size of the fund at the beginning of the month. The independent variables are *Performance Terciles*, where performance is the fractile ranking of Carhart four factor adjusted quarterly return (where the adjustment is based on rolling betas estimates over the prior 36 months). *Lagged Outflows* represent lags 1 through 12 of the dependent variable. *LnAge* is the natural log of the number of months that the fund is in the CRSP database. *Multiclass* is an indicator variable that takes the value of one if the fund offers more than one share class, and is zero otherwise. *LnSize* is the natural log of the fund's total net asset at the beginning of the month. *StdRet* is the standard deviation of the fund's abnormal monthly returns over the previous 12 months. *ExpenseRatio* is the expense ratio over the six month N-SAR reporting period. *EffectiveFrontLoad* is the money that the fund collected from the front-end load over the six month reporting period divided by the amount of new money flowing into the fund over the same six month reporting period. *EffectiveRedemptionFee* is the money generated from the fund's redemption fee over the six month reporting period divided by the amount of money withdrawn from the fund during the same six month reporting period. *EffectiveCDSC* is the money collected from the fund's contingent deferred sales charges over the six month reporting period divided by the amount of money withdrawn from the fund during the same six month reporting period. *12b-1 Fee* is the money generated for the fund from 12-b1 fees over the six month reporting period divided by the size of the fund at the time of the N-SAR filing. t-statistics are in parentheses. Significance is based on Newey-West standard errors in Fama-MacBeth regressions and Rogers standard errors clustered by time in Pooled OLS regressions. ** indicates significance at the 1% level. * indicates significance at the 5% level.

	Fama/MacBeth		Pooled OLS	
	(1)	(2)	(3)	(4)
Intercept	0.023**	0.004**	0.032**	0.005**
	(11.90)	(4.79)	(16.80)	(4.43)
Worst Performance	-0.014**	-0.004**	-0.020**	-0.005**
Tercile	(-6.05)	(-3.02)	(-7.80)	(-3.12)
Middle Performance	-0.005*	-0.002	-0.005*	-0.002
Tercile	(-2.61)	(-1.99)	(-2.53)	(-1.91)
Best Performance	0.023**	0.003	0.028**	0.005*
Tercile	(8.19)	(1.87)	(10.50)	(2.53)
LnAge	-0.001**	-0.0002	-0.002**	-0.0003
	(-6.49)	(-1.68)	(-8.10)	(-1.70)
Multiclass	0.002**	0.001*	0.0004	0.0002
	(5.31)	(2.23)	(1.49)	(0.74)
lnSize	0.00002**	0.00002	0.0004**	0.00003
	(3.77)	(0.36)	(2.97)	(0.26)
StdRet	2.592**	0.227**	1.408**	0.047
	(13.40)	(2.74)	(16.10)	(0.67)
ExpenseRatio	0.731**	0.125**	0.544**	0.106*
	(10.60)	(3.64)	(8.18)	(2.19)
EffectiveFrontLoad	-0.498**	-0.068**	-0.477**	-0.063**
	(-31.80)	(-7.59)	(-31.40)	(-6.30)
EffectiveRedemptionFee	1.797**	-0.443	0.479*	-0.332**
	(4.50)	(-1.55)	(2.36)	(-2.80)
EffectiveCDSC	-0.627**	-0.136**	-0.516**	-0.122**
	(-12.80)	(-5.07)	(-14.10)	(-6.45)
12b-1 Fee	0.683**	0.076	0.745**	0.087
	(6.65)	(0.99)	(7.46)	(1.24)
Lagged Outflows Included?	No	Yes	No	Yes
Adj-R^2	0.09	0.60	0.06	0.57

Table 4. Inflows to Domestic Equity Funds. This table presents results from Fama-MacBeth and Pooled OLS regressions on our sample of 2,619 domestic equity mutual funds. There are 103,631 fund month observations from April 1997 to June 2003. The dependent variable is inflow, which is the amount of new money invested in the fund over a month, divided by the size of the fund at the beginning of the month. The independent variables are *Performance Terciles,* where performance is the fractile ranking of Carhart four factor adjusted quarterly return (where the adjustment is based on rolling betas estimates over the prior 36 months). *Lagged Inflows* represent lags 1 through 12 of the dependent variable. *LnAge* is the natural log of the number of months that the fund is in the CRSP database. *Multiclass* is an indicator variable that takes the value of one if the fund offers more than one share class, and is zero otherwise. *LnSize* is the natural log of the fund's total net asset at the beginning of the month. *StdRet* is the standard deviation of the fund's abnormal monthly returns over the previous 12 months. *ExpenseRatio* is the expense ratio over the six month N-SAR reporting period. *EffectiveFrontLoad* is the money that the fund collected from the front-end load over the six month reporting period divided by the amount of new money flowing into the fund over the same six month reporting period. *EffectiveRedemptionFee* is the money generated from the fund's redemption fee over the six month reporting period divided by the amount of money withdrawn from the fund during the same six month reporting period. *EffectiveCDSC* is the money collected from the fund's contingent deferred sales charges over the six month reporting period divided by the amount of money withdrawn from the fund during the same six month reporting period. *12b-1 Fee* is the money generated for the fund from 12-b1 fees over the six month reporting period divided by the size of the fund at the time of the N-SAR filing. t-statistics are in parentheses. Significance is based on Newey-West standard errors in Fama-MacBeth regressions and Rogers standard errors clustered by time in Pooled OLS regressions. ** indicates significance at the 1% level. * indicates significance at the 5% level.

	Fama/MacBeth		Pooled OLS	
	(1)	(2)	(3)	(4)
Intercept	0.096**	0.017**	0.105**	0.020**
	(25.60)	(8.12)	(23.90)	(6.67)
Worst Performance	0.006	0.003	0.001	0.003
Tercile	(1.86)	(1.22)	(0.34)	(1.11)
Middle Performance	-0.004	0.001	-0.005	0.002
Tercile	(-1.74)	(0.32)	(-1.95)	(0.91)
Best Performance	0.078**	0.026**	0.086**	0.032**
Tercile	(15.80)	(9.81)	(12.80)	(6.89)
LnAge	-0.007**	0.00004	-0.008**	0.0002
	(-16.10)	(0.14)	(-17.00)	(0.54)
Multiclass	0.003**	0.001	0.001	0.001
	(4.22)	(1.52)	(1.17)	(1.40)
lnSize	-0.002**	-0.001**	-0.002**	-0.001**
	(-10.80)	(-8.27)	(-7.45)	(-8.32)
StdRet	2.714**	0.682**	1.640**	0.060
	(8.15)	(3.04)	(5.50)	(0.17)
ExpenseRatio	-1.328**	-0.391**	-1.505**	-0.437**
	(-16.60)	(-7.89)	(-14.40)	(-5.62)
EffectiveFrontLoad	-0.287**	-0.087**	-0.222**	-0.075**
	(-8.63)	(-5.25)	(-6.14)	(-3.25)
EffectiveRedemptionFee	4.076**	0.249	2.009**	-0.190
	(6.44)	(0.60)	(5.21)	(-0.90)
EffectiveCDSC	-0.169*	-0.085	-0.169**	-0.058
	(-2.47)	(-1.25)	(-2.65)	(-0.88)
12b-1 Fee	1.866**	0.379**	1.774**	0.333**
	(12.60)	(3.33)	(11.90)	(2.66)
Lagged Inflows Included?	No	Yes	No	Yes
Adj-R^2	0.09	0.54	0.06	0.42

Table 5. Outflows and Inflows to Domestic Equity Funds While Controlling for Flows in the Opposite Direction. This table presents results from Fama-MacBeth and Pooled OLS regressions on our sample of 2,619 domestic equity mutual funds. There are 103,631 fund month observations from April 1997 to June 2003. The dependent variables are *outflow*, which is the amount of money withdrawn from the fund over a month, divided by the size of the fund at the beginning of the month, and inflow, which is the amount new money invested with the fund over the month, divided by the size of the fund at the beginning of the month. The independent variables are *Performance Terciles,* where performance is the fractile ranking of Carhart four factor adjusted quarterly return (where the adjustment is based on rolling betas estimates over the prior 36 months). *Lagged Outflows* and *Lagged Inflows* represent lags 1 through 12 of the dependent variables. *LnAge* is the natural log of the number of months that the fund is in the CRSP database. *Multiclass* is an indicator variable that takes the value of one if the fund offers more than one share class, and is zero otherwise. *LnSize* is the natural log of the fund's total net asset at the beginning of the month. *StdRet* is the standard deviation of the fund's abnormal monthly returns over the previous 12 months. *ExpenseRatio* is the expense ratio over the six month N-SAR reporting period. *EffectiveFrontLoad* is the money that the fund collected from the front-end load over the six month reporting period divided by the amount of new money flowing into the fund over the same six month reporting period. *EffectiveRedemptionFee* is the money generated from the fund's redemption fee over the six month reporting period divided by the amount of money withdrawn from the fund during the same six month reporting period. *EffectiveCDSC* is the money collected from the fund's contingent deferred sales charges over the six month reporting period divided by the amount of money withdrawn from the fund during the same six month reporting period. *12b-1 Fee* is the money generated for the fund from 12-b1 fees over the six month reporting period divided by the size of the fund at the time of the N-SAR filing. t-statistics are in parentheses. Significance is based on Newey-West standard errors in Fama-MacBeth regressions and Rogers standard errors clustered by time in Pooled OLS regressions. ** indicates significance at the 1% level. * indicates significance at the 5% level.

	Outflows		Inflows	
	Fama/MacBeth	Pooled OLS	Fama/MacBeth	Pooled OLS
Intercept	-0.006**	-0.005**	0.021**	0.023**
	(-6.76)	(-3.98)	(9.63)	(7.72)
Worst Performance	-0.007**	-0.007**	0.009**	0.011**
Tercile	(-4.61)	(-4.53)	(4.00)	(3.98)
Middle Performance	-0.003*	-0.002*	0.001	0.003
Tercile	(-2.25)	(-2.18)	(0.91)	(1.61)
Best Performance	-0.006**	-0.004*	0.028**	0.032**
Tercile	(-3.60)	(-2.18)	(10.30)	(7.16)
Contemporaneous	0.184**	0.169**		
Inflows	(22.30)	(14.70)		
Contemporaneous			0.416**	0.464**
Outflows			(24.60)	(22.70)
LnAge	0.001**	0.001**	-0.001**	-0.001*
	(5.47)	(3.71)	(-2.70)	(-2.26)
Multiclass	0.0002	0.0002	0.0004	0.001
	(0.68)	(0.06)	(0.88)	(1.00)
lnSize	0.0003**	0.0002*	-0.001**	-0.001**
	(4.20)	(2.43)	(-10.50)	(-10.20)
StdRet	0.180*	0.032	0.101	-0.201
	(2.11)	(0.48)	(0.45)	(-0.59)
ExpenseRatio	0.402**	0.385**	-0.802**	-0.875**
	(11.00)	(7.87)	(-14.80)	(-10.50)
EffectiveFrontLoad	-0.085**	-0.085**	0.054**	0.091**
	(-9.58)	(-8.68)	(3.25)	(3.64)
EffectiveRedemptionFee	-0.603*	-0.358**	0.529	0.104
	(-2.34)	(-3.30)	(1.36)	(0.51)
EffectiveCDSC	-0.185**	-0.147**	0.140*	0.142*
	(-7.53)	(-8.72)	(2.34)	(2.42)
12b-1 Fee	-0.070	-0.059	0.349**	0.234
Lagged Outflows Included?	Yes	Yes	No	No
Lagged Inflows Included?	No	No	Yes	Yes
Adj-R^2	0.66	0.62	0.59	0.48

Table 6. Outflows and Inflows to Domestic Equity Funds While Controlling for Flows in the Opposite Direction - Quarterly Observations. This table presents results from Fama-MacBeth and Pooled OLS regressions on our sample of 2,619 domestic equity mutual funds. There are 31,117 fund quarter observations from July 1997 to June 2003. The dependent variables are outflow, which is the amount of money withdrawn from the fund over a quarter, divided by the size of the fund at the beginning of the quarter, and inflow, which is the amount new money invested with the fund over the quarter, divided by the size of the fund at the beginning of the quarter. The independent variables are *Performance Terciles,* where performance is the fractile ranking of Carhart four factor adjusted quarterly return (where the adjustment is based on rolling betas estimates over the prior 36 months). *Lagged Outflows and Inflows* represent lags 1 through 4 of the dependent variables. *LnAge* is the natural log of the number of quarters that the fund is in the CRSP database. *Multiclass* is an indicator variable that takes the value of one if the fund offers more than one share class, and is zero otherwise. *LnSize* is the natural log of the fund's total net asset at the beginning of the quarter. *StdRet* is the standard deviation of the fund's abnormal monthly returns over the previous 12 months. *ExpenseRatio* is the expense ratio over the six month N-SAR reporting period. *EffectiveFrontLoad* is the money that the fund collected from the front-end load over the six month reporting period divided by the amount of new money flowing into the fund over the same six month reporting period. *EffectiveRedemptionFee* is the money generated from the fund's redemption fee over the six month reporting period divided by the amount of money withdrawn from the fund during the same six month reporting period. *EffectiveCDSC* is the money collected from the fund's contingent deferred sales charges over the six month reporting period divided by the amount of money withdrawn from the fund during the same six month reporting period. *12b-1 Fee* is the money generated for the fund from 12-b1 fees over the six month reporting period divided by the size of the fund at the time of the N-SAR filing. t-statistics are in parentheses. Significance is based on Newey-West standard errors in Fama-MacBeth regressions and Rogers standard errors corrected for clustering by time in Pooled OLS regressions. ** indicates significance at the 1% level. * indicates significance at the 5% level.

	Outflows		Inflows	
	Fama/MacBeth	Pooled OLS	Fama/MacBeth	Pooled OLS
Intercept	-0.016*	-0.012**	0.070**	0.074**
	(-2.74)	(-3.31)	(9.29)	(11.70)
Worst Performance	-0.023*	-0.029**	0.032*	0.049**
Tercile	(-2.50)	(-5.47)	(2.81)	(5.22)
Middle Performance	-0.003	-0.004	0.001	-0.004
Tercile	(-0.57)	(-0.87)	(0.09)	(-0.49)
Best Performance	-0.031**	-0.027**	0.113**	0.127**
Tercile	(-4.97)	(-5.14)	(7.25)	(13.80)
Contemporaneous	0.225**	0.222**		
Inflows	(16.50)	(61.30)		
Contemporaneous			0.561**	0.601**
Outflows			(24.70)	(60.10)
lnAge	0.003**	0.003**	-0.004*	-0.004**
	(3.85)	(5.46)	(-2.57)	(-3.77)
Multiclass	-0.0002	-0.001	0.003	0.004*
	(-0.24)	(-1.28)	(1.18)	(2.47)
lnSize	0.001	0.001*	-0.003**	-0.004**
	(1.43)	(2.21)	(-9.89)	(-9.50)
StdRet	0.782	0.203	1.075	-0.715**
	(1.72)	(1.83)	(0.66)	(-3.66)
ExpenseRatio	1.379**	1.380**	-3.440**	-3.542**
	(6.62)	(12.50)	(-11.50)	(-18.30)
EffectiveFrontLoad	-0.309**	-0.318**	0.300**	0.242**
	(-6.11)	(-6.08)	(3.48)	(2.64)
EffectiveRedemptionFee	-1.110	-1.539**	2.418	0.477
	(-1.05)	(-3.64)	(1.33)	(0.64)
EffectiveCDSC	-1.023**	-0.888**	0.834*	0.791**
	(-7.42)	(-5.92)	(2.68)	(3.00)
12b-1 Fee	0.132	-0.026	1.609*	1.730**
	(0.40)	(-0.10)	(2.76)	(3.62)
Lagged Outflows Included?	Yes	Yes	No	No
Lagged Inflows Included?	No	No	Yes	Yes
Adj-R^2	0.71	0.69	0.66	0.6

Figure 1: Flow performance relation
Each month, mutual funds were ranked based on their monthly performance into 20 groups. We report the mean net flow, inflow and outflow for each group over the subsequent month.

Panel A: Mean performance and flows

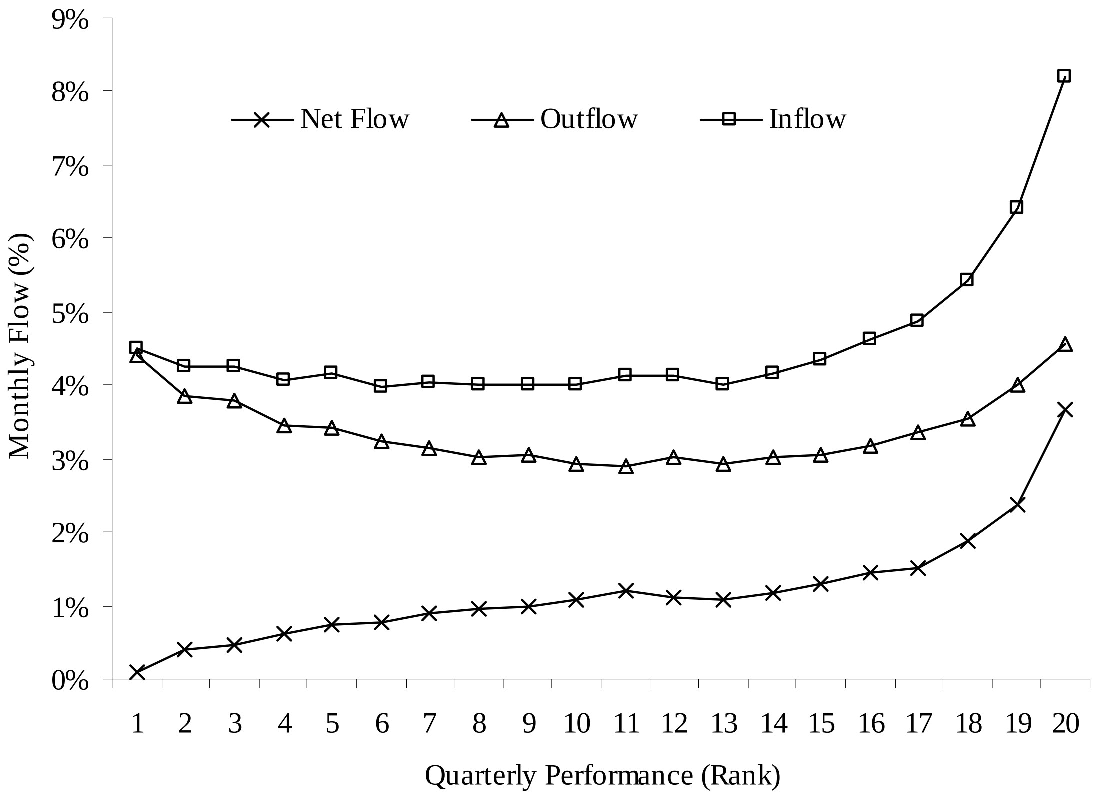


Figure 2: Estimated Monthly Outflows and Inflows

Based on the coefficients obtained from the Fama-MacBeth regressions in Tables 3, 4 and 5, estimated outflow and inflow were calculated from our different model specifications by setting the non-performance variables to their means and only varying the performance ranking from 0 to 1. Panels A1 and B1 represent estimated outflow and inflow from the specifications containing only performance fractiles, and controls as regressors. Panels A2 and B2 represent estimated outflow and inflow from the specifications containing performance fractiles, lagged outflows and inflows respectively, and controls, as regressors. Panels A3 and B3 represent estimated outflow and inflow from the specifications containing performance fractiles, lagged and contemporaneous, outflows and inflows, and controls, respectively, as regressors.

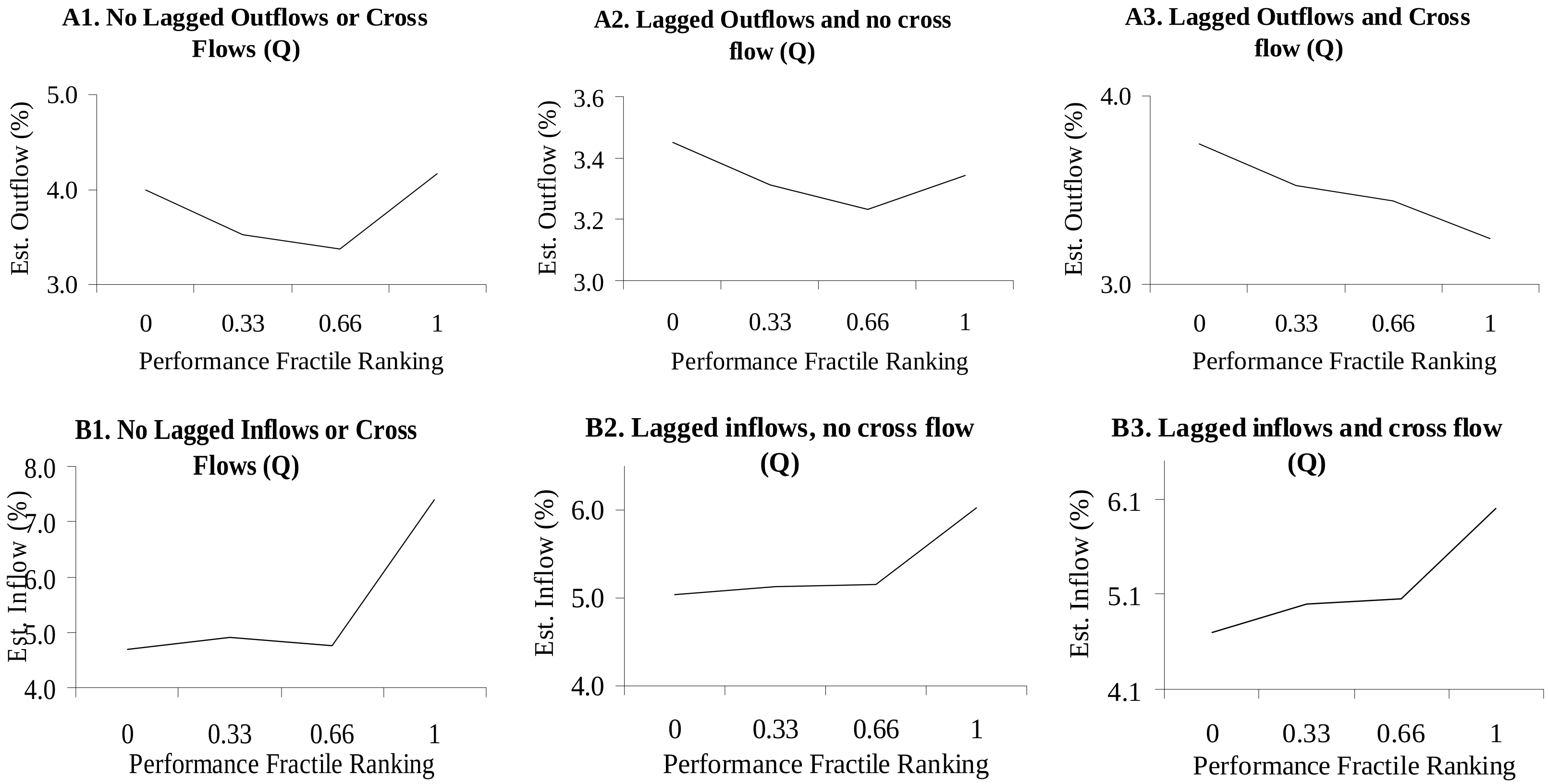
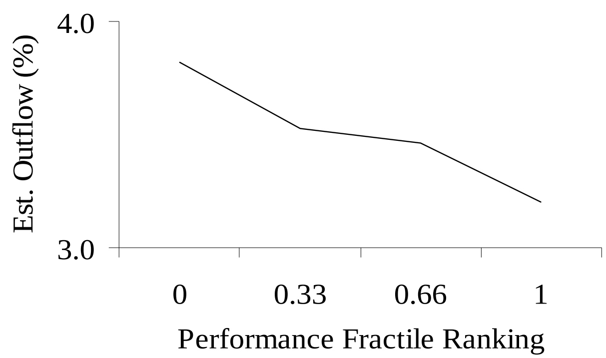


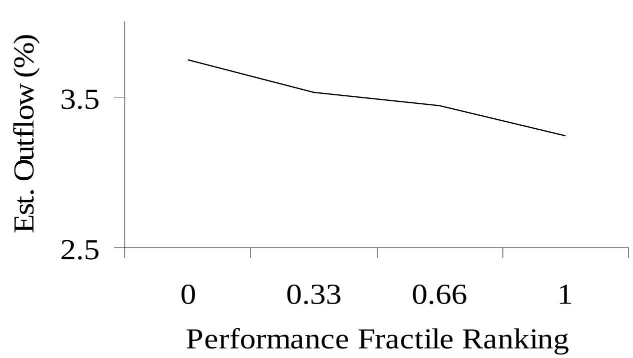
Figure 3: Estimated Monthly Outflows and Inflows, with various performance windows

To ensure the robustness of our findings we re-run our Table 5 analysis, using semi-annual, and annual performance, controlling for lagged flows and contemporaneous cross flows. Based on the coefficients obtained we estimate outflow and inflow by setting the non-performance variables to their means and varying the performance ranking from 0 to 1. Panel C3 represents the relationship between semi-annual performance ranking and monthly outflows. Panel D3 represents the relationship between annual performance and monthly outflows. Panel E3 represents the relationship between semi-annual performance ranking and monthly inflows. Panel F3 represents the relationship between annual performance and monthly inflows.

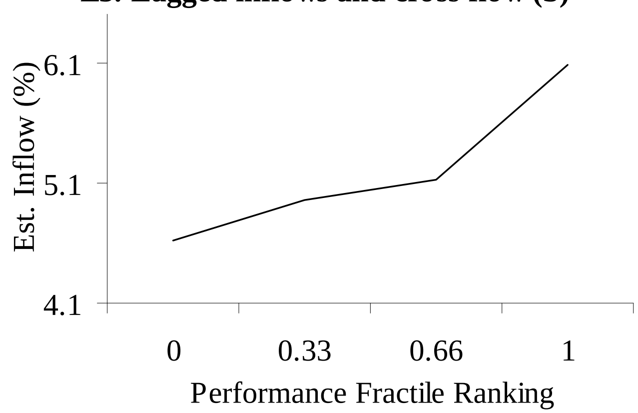
C3. Lagged Outflows and Cross flow (S)



D3. Lagged Outflows and Cross flow (A)



E3. Lagged inflows and cross flow (S)



F3. Lagged inflows and cross flow (A)

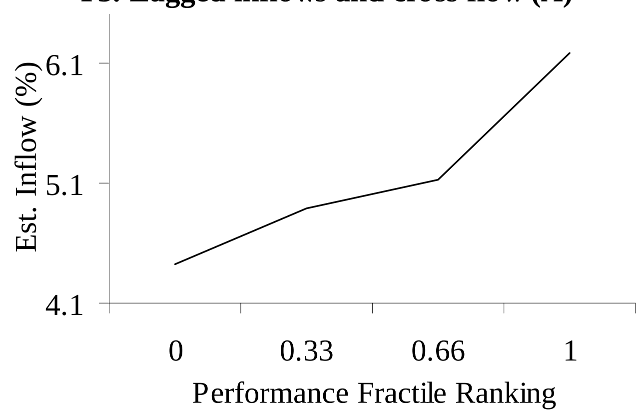


Figure 4: Estimated Quarterly Outflows and Inflows

Based on the coefficients obtained from Fama-MacBeth regressions for quarterly flow data (Table 6), estimated outflow and inflow were calculated for different specifications by setting the non-performance variables to their means and only varying the performance ranking from 0 to 1. Panels A1 and B1 represent estimated outflow and inflow from the specifications containing only performance fractiles as regressors. Panels A2 and B2 represent estimated outflow and inflow from the specifications containing performance fractiles and lagged outflows and inflows respectively, as regressors. Panels A3 and B3 represent estimated outflow and inflow from the specifications containing performance fractiles, lagged and contemporaneous, outflows and inflows, respectively, as regressors.