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Fund Flow Volatility and Performance

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Abstract

This paper provides a detailed analysis of the impact of daily mutual fund flow volatility on fund performance. I document a significant negative relationship between the volatility of daily fund flows and cross-sectional differences in risk-adjusted performance. This relationship is driven by domestic equity funds, as well as small funds, well-performing funds, and funds that experience inflows over the sample period. My results are consistent with performance differences arising from the transaction costs of nondiscretionary trading driven by daily fund flows, but not with performance differences arising from the suboptimal cash holdings that arise from fund flows.

I. Introduction

Open-end mutual funds in the United States possess two characteristics that distinguish them from most other types of investments. First, the daily net asset value (NAV) pricing mechanism of mutual funds provides investors with a large amount of liquidity that is not available when holding securities directly. In most no-load funds, investors may buy or sell shares at a fixed price each day without paying commissions or bid-ask spreads and with few limits on the depth or the number of shares they may trade. Investors do not pay for this liquidity directly. Instead, the costs are paid by all shareholders in the fund and are reflected in lower fund returns. This brings me to the second interesting characteristic of open-end mutual funds—that they tend to underperform their benchmarks (Sharpe (1966), Jensen (1968), Ippolito (1989), Malkiel (1995), and Gruber (1996)). High transaction costs have been suggested as a reason for this underperformance (Grinblatt

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and Titman (1989), Chalmers, Edelen, and Kadlec (2001a), Edelen (1999), and Wermers (2000)), but the exact factors driving these costs have not been fully examined. Johnson (2004) shows that short-term fund shareholders impose higher liquidity costs on a fund than long-term shareholders, consistent with transaction costs arising from short-term fund flows being an important factor driving cross-sectional differences in performance. This study analyzes high-frequency trading by a fund's investors and argues that the flow volatility caused by trading is related to a fund's performance.

There are several reasons to expect that fund performance could be affected by erratic fund flows ("flows" here are defined as net daily purchases or redemptions by a fund's shareholders). Flows can cause a fund manager to trade more frequently, incurring transaction costs, such as commissions and having to pay bid-ask spreads. Another possibility is that flows will constrain a manager from following her optimal investment strategy. For example, if market prices decline and a manager wishes to purchase securities, she may instead be forced to sell in order to pay redeeming shareholders. If the fund manager chooses not to hold enough cash to meet unexpected redemptions, then she faces the risk of acting as a liquidity trader in response to fund flows and therefore can be expected to suffer losses to more informed traders (Kyle (1985)).

A fund manager's main option to avoid liquidity trading is to hold excess levels of cash to meet unexpected redemptions. However, holding cash also depresses performance during periods of positive returns due to the low returns on cash holdings (Ferson and Warther (1996)). This situation is referred to here as "cash drag." Even if a fund manager responds to unexpected flows in other manners, such as through lines of credit, the costs are still nonzero and should be proportional to the amount of unexpected flows. Furthermore, the calculation of mutual fund prices by NAV leads to short-term predictabilities in prices that can be exploited by investors, with costs paid by the fund's nontrading shareholders through lower overall performance (Greene and Hodges (2002), Chalmers et al. (2001b), Goetzmann, Ivkovic, and Rouwenhorst (2001), Zitzewitz (2003), and Bhargava and Dubofsky (2001)). This will also result in unexpected or volatile flows having a negative impact on fund performance.

Of course, not all investors trade frequently enough to make short-term flows so volatile that they impact performance. However, all investors need not trade frequently for such effects to manifest themselves. It is only necessary for different investors to trade often enough so that flows reach levels where they influence a fund manager's trading and allocation strategies. Not all of these flows will end up as fund trading, but if only a small amount does, then this can represent substantial transaction costs, or trading constraints, that must be incurred by fund managers. However, it is an open question as to whether these daily flows are a significant factor influencing returns, which is the primary question that this study addresses. The possibility that fund flows are impacting returns gives this study its research hypothesis:

Flow Volatility Hypothesis. Daily fund flow volatility is negatively related to cross-sectional differences in performance.

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The alternative to this is that flow volatility does not add any power to explain differences in performance once cash holdings, turnover, and standard control variables have been corrected for. Cross-sectional regressions testing the above hypothesis make up the bulk of the analysis presented here. In addition to flow volatility, I also examine if unexpected daily flows are negatively related to fund performance.

My results indicate that both flow volatility and unexpected flows are negatively related to fund performance and confirm my hypothesis. However, while this finding applies to funds in general, there are important subsets of my sample that drive this relationship. In particular, domestic equity funds, small funds, well-performing funds, and funds that experience net cash inflows provide the strongest evidence of a negative relationship between daily flow volatility and performance.

These results provide several important extensions to the findings of Edelen (1999), who demonstrates that unexpected monthly fund flows are correlated with underperformance for domestic equity mutual funds. First, I show how the relationship between flow volatility differs across alternate investment objectives and with several fund characteristics. Second, I provide 2 new high-frequency measures to proxy for the potential trading costs of fund flows: daily flow volatility and unexpected daily flows. These measures have not been used at this frequency in evaluating fund performance and are a more direct measure of a fund's potential liquidity-driven trading costs than the monthly flows examined by Edelen (1999). Most importantly, I demonstrate the importance of these measures, and thus a fund's probable trading transaction costs, as a factor in mutual fund underperformance, as opposed to the portfolio reallocation decisions that would likely be driven by the longer-term flows employed by Edelen (1999).

These findings suggest that the pricing structure of mutual funds and the liquidity provided have important effects on fund performance. Mutual funds cannot be viewed simply as collections of individual securities, as their prices and transaction costs do not represent the sum of these costs for each security in the portfolio. Investors should consider both the costs and benefits of this liquidity option that they are purchasing when entering a mutual fund. Fund managers must recognize that their performance is tied to the behavior of their investors, and not simply to their ability to choose securities. Managers have often been accused of trading excessively, due to possible agency problems (Lakonishok, Shleifer, and Vishny (1992), Shapira and Venezia (2001), and Brown (1996)). However, the interaction of turnover, fund flows, and performance documented here is consistent with fund managers trading excessively, not because they are attempting to "churn" the portfolio, but because they must trade in order to manage investors' liquidity demands.

This study proceeds as follows. Section II describes the data set employed, and Section III presents the cross-sectional analysis of daily fund flow volatility and performance. Section IV describes robustness tests for the primary cross-sectional analysis, while Section V discusses the impact of alternative calculations of daily flow. Section VI extends the analysis to fund groups, Section VII to investment objectives, and conclusions are presented in Section VIII.

II. Data

Data from several sources are used to characterize fund flow volatility and its impact on fund performance. Lipper provides daily data from March 2000 until October 2006 on mutual fund total net assets (TNA) and returns (adjusted for distributions), which are used to calculate daily flows. Although Lipper reports daily ending TNA for each fund, this TNA figure does not include the day's net fund flows. Therefore, I calculate daily flows as

$$c_t \quad = \quad \frac{a_{t+1}}{1+r_{t+1}} - a_t, \tag{1}$$

where a_t is total net assets on day t, r_t is the fund's return on day t, and c_t is fund flow on day t. To get percentage flows, I then divide equation (1) by $a_t/(1+r_t)$. Fund flow volatility (SD_FLOW) is measured by the standard deviation of daily percentage fund flows over the sample period. Further procedures for verifying the accuracy of TNA observations and the calculation of daily flows are discussed later in this section.

Cross-sectional variables are taken from the Center for Research in Security Prices (CRSP) mutual fund database for each year of my sample period. Expense ratios are decomposed into 12b-1 (12B_1) and non-12b-1 (NON_12B_1) components. Load fees are classified as front (FRONT) or deferred (DEFER). The measure of fund size (SIZE) used in my analysis is the natural logarithm of a fund's average daily TNA. Fund turnover ratios (TURNOVER) are used as a measure of a fund's potential transaction costs, and cash holdings (CASH) represents the percentage of the fund's assets held in cash and cash equivalents, as a measure of liquidity. My primary measure of performance is the intercept (α_i) from a 3-factor model of daily returns.[1]

Different share classes of the same fund are treated as separate funds due to the different flows, loads, and fees of each share class. I put the data through rigorous screens for errors, eliminating extreme observations (absolute flows of greater than 50% per day), and manually checking the remaining extreme observations for validity. I delete all funds with average daily TNA of less than $10 million due to the extremely erratic nature of percentage flows for these funds. The sample is restricted to domestic equity, domestic bond, and international equity investment objectives. Funds with less than 800 daily observations are eliminated from the analysis.

Table 1 describes my sample. Average daily percentage flows are approximately 16.5 basis points (bp) of TNA, while the average standard deviation (my measure of flow volatility) is about 4% of TNA each day. While average daily flows are positive, there is considerable variation in the behavior of flows across funds, with only 60% of funds in the sample displaying positive average daily

[1]The 3 factors are calculated from daily returns using the standard model of Fama and French (1992), with data from Ken French's Web site (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html). I use these U.S.-based equity factors due to the fact that most U.S. mutual funds' shares are owned by U.S. households (ICI (2006)). I prefer to use a common benchmark so that I may compare the impact of flow volatility across investment objectives while holding constant the method of performance measurement.

flows. Average (median) fund size is \$297 million (\$85 million). The average (median) raw return is 2.19 bp (2.32 bp) per day, with annual average (median) returns of 5.07% (5.27%). The average (median) 3-factor-adjusted performance measure is 1.11 bp (1.25 bp) per day. Keep in mind that I include all investment objectives in the sample, and so comparisons with previous performance studies of only domestic equity funds are not appropriate. For the typical fund, the distribution of daily flows (not reported) are nonnormal, with positive skewness and more weight in the tails.

TABLE 1

Descriptive Statistics of Cross-Sectional Characteristics

Table 1 presents descriptive statistics for the sample of 4,772 open-end mutual funds over the sample period from March 2000 to October 2006. Daily fund flows, returns, and total net assets (TNA) are from Lipper, while annual data are from CRSP. [a]percentage greater than 1%; [b]percentage greater than \$100 million; [c]percentage greater than 100%.

	Averages	Medians	% of Funds > 0
Panel A. Flow			
Average daily flow (%)	0.1646	0.0277	60.0
Standard deviation of daily flow (%)	3.97	1.18	60.9[a]
Average daily flow (\$thousands)	11.59	4.78	55.1
Average annual flow (%)	25.56	11.13	55.1
Average annual flow (\$millions)	18.83	5.71	55.1
Panel B. Returns			
Average daily return (%)	0.0219	0.0232	83.4
Average annual return (%)	5.07	5.27	80.0
Average 3-factor alpha, daily (%)	0.0111	0.0125	69.9
Panel C. Fund Characteristics			
Size (\$millions)	297.32	84.57	45.5[b]
Cash holdings (%)	4.36	3.03	95.5
Turnover (%)	97.18	68.80	32.9[c]
12b-1 fees (%)	0.41	0.25	68.0
Non-12b-1 fees (%)	0.99	0.97	100.0
Front load (%)	1.39	0.00	32.7
Deferred load (%)	1.16	0.43	53.9

III. Cross-Sectional Regression Analysis

My regression analysis is performed with the control variables commonly used in published studies of fund performance (Ippolito (1989), Malkiel (1995), Gruber (1996), Carhart (1997), Chevalier and Ellison (1999a), (1999b), and Chalmers et al. (2001a)). My primary model seeks to explain cross-sectional differences in fund performance and takes the form

$$(2) \qquad \alpha_i = \beta_0 + \beta_1 \mathrm{SD\_FLOW}_i + \beta_2 \mathrm{MEAN\_FLOW}_i + \beta_3 \mathrm{SIZE}_i + \beta_4 \mathrm{FRONT}_i + \beta_5 \mathrm{DEFER}_i + \beta_6 \mathrm{12B\_1}_i + \beta_7 \mathrm{NON\_12B\_1}_i + \beta_8 \mathrm{TURNOVER}_i + \beta_9 \mathrm{CASH}_i + e_i.$$

Results from the ordinary least squares (OLS) estimation[2] of this model are presented in column 1 of Table 2, where one can see that flow volatility takes

[2]For scaling purposes, flows and returns are entered as percentages while decimals are used for fees and turnover.

a significant negative coefficient. Consistent with previous studies, average daily flows take a significant positive coefficient. Fees, size, and turnover take significant negative coefficients, while front-end loads take a positive coefficient. The R^2 measure indicates that about 6.6% of the variation in performance is explained. Overall, these results support the flow volatility hypotheses.

TABLE 2

Cross-Sectional Regression Analysis

Table 2 presents the results of OLS and 2SLS regressions explaining cross-sectional differences in performance for the full sample of 4,772 open-end mutual funds. Here, α_i is the intercept from a daily 3-factor model of fund i's returns; SD_FLOW is the standard deviation of daily percentage flows; expense ratios are decomposed into 12B_1 and NON_12B_1 fees; SIZE is the natural log of average daily total net assets. In models (2) and (4), SD_FLOW is replaced with UNEXPECTED_DAILY_FLOW, the root mean squared error from a model of expected daily flows. Heteroskedasticity and autocorrelation consistent (HAC) (White (1980)) t-statistics are given in parentheses. The instruments used in the 2SLS models include lagged values of all model variables plus indicators for investment objectives. Lagged values are obtained from the panel of funds each year over the 6-year sample period. Pooled 2SLS is used in models (3) and (4) with the endogenous variables being flow volatility (SD_FLOW), unexpected flows (UNEXPECTED_DAILY_FLOW), average daily flow (MEAN_FLOW), turnover (TURNOVER), and cash holdings (CASH). * and ** indicate significance at the 5% and 1% levels, respectively. The general model is

$$\begin{aligned}(2)\qquad \alpha_i \;=\;& \beta_0 + \beta_1\text{SD\_FLOW}_i + \beta_2\text{MEAN\_FLOW}_i + \beta_3\text{SIZE}_i + \beta_4\text{FRONT}_i + \beta_5\text{DEFER}_i\\ &+ \beta_6\text{12B\_1}_i + \beta_7\text{NON\_12B\_1}_i + \beta_8\text{TURNOVER}_i + \beta_9\text{CASH}_i + e_i.\end{aligned}$$

	OLS		2SLS	
Independent Variables	(1)	(2)	(3)	(4)
Intercept	0.0256**	0.0256**	0.0220**	0.0212**
	(18.71)	(18.69)	(6.58)	(8.60)
SD_FLOW	–0.0055*	—	–0.0067*	—
	(–2.41)		(2.18)	
UNEXPECTED_DAILY_FLOW	—	–0.0046*	—	–0.0077**
		(–2.01)		(–3.76)
MEAN_FLOW	0.0626**	0.0539**	0.1408	0.1049
	(3.01)	(2.72)	(0.44)	(0.54)
SIZE	–0.0006**	–0.0006**	–0.0008	–0.0002
	(–3.25)	(–3.26)	(–0.18)	(–0.75)
TURNOVER	–0.0010**	–0.0009**	0.00239	0.0066**
	(–3.54)	(–3.52)	(0.85)	(2.94)
DEFER	–0.0021	–0.0023	0.0232	0.0488
	(–0.09)	(–0.10)	(0.44)	(1.21)
FRONT	0.0271*	0.0271*	0.0144	0.0031
	(2.03)	(2.03)	(0.49)	(0.14)
12B_1	–0.3192**	–0.3166**	–0.2389	–0.5136**
	(–3.22)	(–3.19)	(–1.01)	(–2.85)
NON_12B_1	–1.0832**	–1.0829**	–0.4771**	–0.3811**
	(–10.12)	(–10.10)	(–2.97)	(–3.16)
CASH	0.0051	0.0047	0.0109	–0.0181
	(1.77)	(1.62)	(0.40)	(–0.91)
R^2	6.6%	6.5%	0.4%	1.8%

IV. Robustness of Cross-Sectional Regression Analysis

My hypothesis that volatile flows act to depress performance is based on the argument that fund managers incur costs from flows that they cannot predict and prepare for. I proxy for these unexpected flows with flow volatility. Another option is to model expected flows and then to use these to compute a more direct measure

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of unexpected daily fund flows. Edelen and Warner (2001) and Warther (1995) both have shown that lagged flows have some predictive power in explaining current short-term aggregate flows. I therefore model expected daily flows for each fund i with a simple autoregressive model of daily flows:

$$(3) \qquad \text{DAILY\_FLOW}_t = \alpha_i + \sum_{a=1}^{5} \beta_{a,i} \text{DAILY\_FLOW}_{t-a,i} + e_i.$$

I then take the root mean squared error from this model as a measure of unexpected fund flows for each fund over the sample period. I experiment with several variations of the model based on different lag lengths, incorporating various assumptions regarding the structure of the error terms and including lagged returns and fund size. These alternative models all yield essentially identical results in my analysis. Therefore I report results only for a simple model incorporating 5 lags of flows and not including lagged returns or lagged TNA. Results for these OLS regressions are reported in model (2) of Table 2 and document that unexpected daily flow also takes a significant negative coefficient in explaining performance.

In addition to using unexpected flows as an alternative to flow volatility, I also examine several alternative measures of performance. I find that both flow volatility and unexpected flows also take significant negative coefficients (not reported) in explaining raw returns, load-adjusted returns, and both 1-factor (market-model) alphas and 4-factor alphas (including a momentum factor). I conduct several further robustness tests, such as using average absolute flows instead of flow volatility and eliminating the control variables. The use of absolute flows is an important robustness check because the possible nonnormality of flows could lead to biases when using the simple standard deviation of flows. Average absolute flows take the same negative signs and at similar significance levels as flow volatility. The elimination of my control variables, either concurrently or one at a time, generally does not change my results for flow volatility or unexpected flows and is therefore not reported. In particular, the elimination of turnover and/or cash holdings does not change the signs or significance of the coefficients for flow volatility or unexpected daily flows.

One motivation for the additional checks concerning the variables for turnover and cash holdings is that they may be endogenous with respect to flows. Therefore I also correct for this possibility by repeating the regressions using two-stage least squares (2SLS) and using lagged values of the indicators for investment objectives as instruments. Turnover, cash holdings, flow volatility/unexpected flow, and average daily flow are the endogenous variables. The inclusion of flow volatility and unexpected flows as endogenous variables is motivated by the possibility that it could be the fund's performance that is driving the behavior of flows. To obtain lagged values, I compute annual values of all variables for each year during the 6-year sample period and estimate a pooled 2SLS to estimate the model. The equation for the endogenous variables is

$$
\begin{aligned}
(4) \qquad \text{ENDOGENOUS\_VARIABLE}_{i,t} \quad = \quad & \beta_0 \\
& + \beta_1 \text{MEAN\_DAILY\_PERCENTAGE\_FLOW}_{i,t-1} \\
& + \beta_2 \text{SD\_FLOW}_{i,t-1} + \beta_3 \text{SIZE}_{i,t-1} + \beta_4 \text{FRONT}_{i,t-1} \\
& + \beta_5 \text{DEFER}_{i,t-1} + \beta_6 \text{12B\_1}_{i,t-1} + \beta_7 \text{NON\_12B\_1}_{i,t-1} \\
& + \beta_8 \text{TURNOVER}_{i,t-1} + \beta_9 \text{CASH}_{i,t-1} \\
& + \beta_{10} \text{INTERNATIONAL\_INDICATOR}_{i,t-1} \\
& + \beta_{11} \text{BOND\_INDICATOR}_{i,t-1} + e_{i,t}.
\end{aligned}
$$

In computing *unexpected flows*, I used lagged *unexpected flows* as an instrument rather than lagged *flow volatility*. Results are presented in models (3) and (4) of Table 2. The results remain qualitatively similar to the OLS regressions, with significant negative coefficients for flow volatility and unexpected flows. The results are robust to various adjustments for the time-series properties of this model, such as including fixed effects for each year. I therefore limit the reported results to the simple pooled 2SLS estimates. The results of the 2SLS regressions are consistent with flow volatility and unexpected flows being negatively related to performance after adjusting for the possible endogeneity of flows.

In order to further examine the causal relationship between flow volatility and performance, I now take the top and bottom quartiles of the sample based on performance, flow volatility, and unexpected flows. Table 3 summarizes the average values for performance, flow volatility, and unexpected flow for these groups. One can observe that the measure of unexpected flow takes values very close to the calculations of flow volatility. The t-tests for significant differences between group means reveal that both high-volatility funds and funds with large levels of unexpected flows have significantly lower average performance. Funds with high risk-adjusted performance do not show significantly different levels of flow volatility or unexpected flows when compared to low-performing funds. An additional observation is that while funds with more volatile flows have higher raw returns, this relationship does not persist once other variables are included in a multivariate regression, as noted earlier. Overall, these findings further support the conclusion that it is flow volatility that is driving differences in performance rather than performance driving flow volatility.

One further explanation for my findings that must be addressed is that an asymmetric flow-performance relationship could lead to a spurious correlation between the standard deviation of flows and performance.[3] This is based on the possibility that the asymmetric flow-performance relationship that has been documented for long-term flows (Chevalier and Ellison (1997), Sirri and Tufano (1999), and Huang, Wei, and Yan (2007)) also applies to my sample of daily data. I therefore test for an asymmetric flow-performance relationship with a piecewise

[3]This analysis is motivated by the following example of spurious correlation generously provided by the editor: There is by now a large literature that has documented an asymmetric relationship between performance and fund flow. This relationship implies a correlation between fund flow volatility and performance. To see this, assume for simplicity that fund excess returns, R, are normally distributed with mean 0 and that this asymmetry is captured by the empirical relation: flow equals aR when $R > 0$, and flow equals 0 when $R \leq 0$. Here, $a > 0$. Then, from the properties of the truncated normal distribution one may infer that the cross-sectional sample correlation between the sample standard deviation of flow and the sample mean of excess return is 0.441 (Johnson and Kotz (1970)).

TABLE 3

Top and Bottom Quartiles of Performance, Flow Volatility, and Unexpected Flows

Table 3 presents average statistics for the top and bottom quartiles of the sample based on performance, flow volatility, and unexpected flows. Performance is measured by the intercept (α) from a 3-factor model of daily returns. Flow volatility (SD_FLOW) is the standard deviation of percentage daily fund flows. Unexpected flows (UNEXPECTED_DAILY_FLOW) are measured by the average root mean squared error from a model of expected daily flows. *t*-tests are for differences in means between the top and bottom quartiles. * and ** represent a significant difference at the 5% and 1% levels, respectively. There are approximately 1,193 funds in each quartile. All figures are reported as percentages.

	Top Quartile Based on Performance	Bottom Quartile Based on Performance
Performance (α)	0.0322**	–0.0124**
Annual return	9.84**	0.10**
SD_FLOW	2.78	3.19
UNEXPECTED_DAILY_FLOW	2.75	3.08
	Top Quartile Based on Flow Volatility (SD_FLOW)	Bottom Quartile Based on Flow Volatility (SD_FLOW)
Performance (α)	0.0094**	0.0183**
Annual return	5.98**	4.73**
SD_FLOW	10.93**	0.48**
UNEXPECTED_DAILY_FLOW	10.74**	0.46**
	Top Quartile Based on Unexpected Flows (UNEXPECTED_DAILY_FLOW)	Bottom Quartile Based on Unexpected Flows (UNEXPECTED_DAILY_FLOW)
Performance (α)	0.0094**	0.0181**
Annual return	6.04**	4.73**
SD_FLOW	10.88**	0.51**
UNEXPECTED_DAILY_FLOW	10.75**	0.46**

linear regression of flow on a fund's performance ranking. Both flows and performance are measured as in the rest of my study (average daily percentage flows and performance ranks based on a 3-factor model). All coefficient estimates for performance ranks are insignificant in these tests, with no patterns in the sign or magnitude of coefficient estimates as one looks across ranks (results available from the author). These tests suggest that there is no asymmetric pattern in flow and performance for my sample of daily data. Therefore, I can be confident that my findings are not driven by any asymmetric pattern between fund flows and performance. However, the lack of an asymmetric relationship between flows and performance does further demonstrate that the behavior of daily fund flows differs substantially from the long-term flow patterns documented by other studies of mutual fund performance.

V. Alternative Calculation of Daily Flows

The Lipper database reports daily TNA not including the current day's flows. Therefore, funds do not suffer from the time constraint that exists when they must report end-of-day TNA including the current day's flows. From these data, I can compute an accurate end-of-day measure of TNA on day t including day t's flows by taking the end-of-day TNA on day $t+1$ and discounting by the return on day $t+1$.

The reliability of funds consistently reporting the current day's net flows is an issue of concern in other databases of daily fund flows such as the Trimtabs database used by Edelen and Warner (2001), Greene and Hodges (2002), Zitzewitz (2003), and Chalmers et al. (2001b). Trimtabs reports daily fund TNAs for many funds that include the current day's net flows. Therefore, flows are calculated as

$$c_t = a_t - [a_{t-1}(1 + r_t)], \tag{5}$$

where a_t is total net assets on day t, r_t is the fund's return on day t, and c_t is fund flow on day t. To get percentage flows, I then divide equation (5) by a_{t-1}. However, this figure for TNA suffers from the problem that funds themselves do not have an accurate measure of their TNA at the end of each trading day. Therefore, some funds actually report TNAs including the current day's flows, while other funds report TNAs not including the current day's flows. Some funds even report TNA partially including the day's flows, with the remaining flows being included in the next day's TNA. This obviously leads to difficulties in accurately calculating daily flows from such data.

There are several reasons why I do not believe that this potential problem should invalidate the results. First, Lipper's procedure of reporting fund TNA not including the day's flows leaves much less potential for misreporting by funds. Second, any discrepancy in the inclusion of flows in the current day's TNA should only result in a one-day bias in daily flows that is correlated with returns from the previous day. Therefore, any bias in the calculation of flow volatility over the sample period should be largely eliminated, as I consider the standard deviation of flows over extended periods of time. Furthermore, because all common mutual fund databases, including CRSP, Lipper, Morningstar, and Trimtabs, round their reported TNA (usually to $100,000s), any error in TNA will tend to be within the rounding difference for most observations. I am therefore confident that the issues concerning TNA reporting that have been raised about past daily flow data are not relevant to this study or to the Lipper database.

In order to fully examine any possible influence of mismeasured TNA, I repeat all analysis with flows calculated assuming that TNA_t includes the current day's flows, as given in equation (5). This actually strengthens the results, with flow volatility and unexpected flows still taking negative coefficients (not reported) for both OLS and 2SLS regressions, but with slightly higher significance levels.

VI. Cross-Sectional Regression Analysis of Fund Groups

While the alternative measures of performance and flow volatility do not lead to major changes in the findings, when I examine certain subgroups from the overall sample I do find variation on the relationship between flow volatility and performance. Because the liquidity of a security is often influenced by the size of the security (Demsetz (1968)), I first split the sample based on fund size. This allows me to examine if the link between flow volatility and performance is driven by the economies of scale faced by the fund manager.

The impact of flows on the fund manager could also differ based on whether there is an inflow or an outflow. Unfortunately I observe only net flows each day, and many of these flows may be reversed before the fund manager is forced to trade. Therefore I split the sample based on the net long-term flows to each fund over the entire sample period. Each fund is classified as a net inflow fund or an outflow fund based on its total cumulative flows. This allows me to examine if there is a long-term difference between cumulative inflows and outflows.

Third, because I know that the link between flow and performance is nonlinear (Sirri and Tufano (1998)), it is also reasonable that the link between flow volatility and performance is nonlinear. As a simple examination of this possibility, I split the sample based on those funds whose risk-adjusted performance is positive and those for which is it negative. I then repeat the basic regression analysis. Results are reported in Table 4.

TABLE 4

Cross-Sectional Regression Analysis

Table 4 presents the results of OLS regressions explaining cross-sectional differences in performance for the sample of 4,772 open-end mutual funds partitioned by total net assets (TNA), relative performance, and average level of flows. Here, α_i is the intercept from a daily 3-factor model of fund i's returns; SD_FLOW is the standard deviation of daily percentage flows; expense ratios are decomposed into 12B_1 and NON_12B_1 fees; SIZE is the natural log of average daily TNA; "Big" funds are those with average TNA greater than the median of $84.57 million; "Inflow" funds are those with positive average monthly flows; "Positive α" funds are those with a positive value for α. * and ** indicate significance at the 5% and 1% levels, respectively. HAC (White (1980)) t-statistics are given in parentheses. The model is

$$\alpha_i = \beta_0 + \beta_1 \text{SD\_FLOW}_i + \beta_2 \text{MEAN\_FLOW}_i + \beta_3 \text{SIZE}_i + \beta_4 \text{FRONT}_i + \beta_5 \text{DEFER}_i + \beta_6 \text{12B\_1}_i + \beta_7 \text{NON\_12B\_1}_i + \beta_8 \text{TURNOVER}_i + \beta_9 \text{CASH}_i + e_i. \tag{2}$$

Independent Variables	Big Funds	Small Funds	Positive α	Negative α	Inflow Funds	Outflow Funds
Intercept	0.0304**	0.0193**	0.0215**	–0.0048	0.0187**	0.0333**
	(12.99)	(6.54)	(19.70)	(–1.83)	(10.63)	(16.11)
SD_FLOW	–0.0052	–0.0090*	–0.0038*	–0.0107	–0.0075*	–0.0027
	(–1.30)	(–2.21)	(–2.28)	(–1.35)	(–2.50)	(–0.87)
MEAN_FLOW	0.1069	0.0767**	0.0421**	0.1529	0.0708*	0.0364
	(1.64)	(2.69)	(2.96)	(0.89)	(2.34)	(1.51)
SIZE	–0.0017**	0.0016*	–0.0007**	0.0007*	–0.0004	–0.0008**
	(–5.09)	(2.31)	(–5.28)	(2.27)	(–0.17)	(–2.79)
DEFER	–0.0500	0.0224**	0.0226	–0.0445	0.0453*	0.0689*
	(–1.57)	(–2.84)	(1.26)	(–1.43)	(–2.38)	(2.18)
FRONT	0.0405*	–0.0028	0.0126	0.0421*	0.0244	0.0266
	(2.51)	(0.72)	(1.15)	(2.22)	(1.37)	(1.40)
12B_1	–0.3242*	–0.2938	–0.4096**	0.5736**	–0.2257	–0.7038**
	(–2.30)	(–0.12)	(–5.22)	(3.96)	(1.38)	(–4.70)
NON_12B_1	–0.8398**	–1.2646*	0.1631	–1.0802**	–0.4458	–2.0653**
	(–5.90)	(–2.14)	(1.79)	(–6.35)	(–1.79)	(–12.89)
TURNOVER	–0.0010*	–0.0009**	0.0001	–0.0014	–0.0010**	–0.0006
	(–2.04)	(–8.28)	(0.35)	(–1.47)	(–3.41)	(–1.87)
CASH	0.0038	0.0065	–0.0086**	0.0042	0.0017	0.0001
	(0.63)	(1.90)	(–4.21)	(0.35)	(0.53)	(0.02)
R^2	6.2%	8.3%	2.2%	10.8%	1.2%	18.2%
N	2,386	2,386	3,594	1,178	2,628	2,144

The results indicate that there is considerable variation across these groups in the relationship between flow volatility and performance. A significant negative coefficient is found for small funds but not large funds, suggesting that the economies of scale present for larger funds are successful in alleviating the problem of volatile fund flows.

Funds with positive risk-adjusted performance display a significant negative coefficient, but not funds with negative risk-adjusted performance. This is consistent with a nonlinear relationship between flow volatility and performance. The finding therefore extends the asymmetric nature of the flow-performance relationship to the second moment of the flow distribution. This conclusion is further supported by the last partition of the sample, between funds that experience net inflows or outflows over the sample period. Here I find that there is a significant negative coefficient for inflow funds but not for funds that experience net outflows. These results are independent of the previously documented link between flow and performance (Chevalier and Ellison (1997), Sirri and Tufano (1999), and Huang et al. (2007)) for several reasons. First, the asymmetry present here is between flow volatility and performance, not simply the level of flow and performance. Second, if the traditional flow-performance relationship were driving the results, then I would expect to find a positive coefficient for flow volatility and performance, while I instead obtain a negative coefficient estimate. Third, as mentioned above, the data do not display a significant asymmetric relationship between daily flow and performance, as is the case for monthly or quarterly flows. Therefore, the asymmetries displayed here are unique to daily data and to the second moment of the flow distribution.

VII. Cross-Sectional Regression Analysis Based on Investment Objectives

For the final cross-sectional tests of daily flow volatility, I partition the sample based on investment objectives as reported in the CRSP mutual funds database, with descriptive statistics reported in Table 5. The sample contains 2,593 domestic equity funds, 1,583 domestic bond funds, and 597 international equity funds.

TABLE 5

Descriptive Statistics of Cross-Sectional Characteristics by Investment Objective

Table 5 presents descriptive statistics for the sample of open-end mutual funds over the sample period from March 2000 to October 2006, by investment objective. Daily fund flows, returns, and TNA are from Lipper, while annual data are from CRSP. * and ** represent a significant difference at the 5% and 1% levels, respectively, in t-tests for differences in means when international equity and bond funds are compared to domestic equity funds.

	Domestic Equity Funds	Domestic Bond Funds	International Equity Funds
Panel A. Flow			
Average daily flow (%)	0.1794	0.1245	0.2063
SD of daily flow (%)	4.22	3.21	4.94
Average daily flow ($thousands)	5.71	−1.72**	72.37*
Average annual flow (%)	25.25	13.90	57.73**
Average annual flow ($millions)	10.07	−1.96**	111.79**
Panel B. Returns			
Average daily return (%)	0.0204	0.0221*	0.0289**
Average annual return (%)	4.35	5.36**	7.87**
Average 3-factor alpha, daily (%)	0.0071	0.0215**	0.0010**
Panel C. Fund Characteristics			
Size ($millions)	333.87	217.84**	349.50
Cash holdings (%)	4.21	4.77*	3.79
Turnover (%)	92.81	108.47**	86.22
12b-1 fees (%)	0.43	0.37**	0.41
Non-12b-1 fees (%)	1.08	0.70**	1.37**
Front load (%)	1.40	1.34	1.54
Deferred load (%)	1.22	1.05**	1.20
N	2,593	1,583	597

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The regression tests proceed as before, with results presented in Table 6. Domestic equity funds take a significant negative coefficient for flow volatility. The coefficient estimates for bond and international funds are also negative,[4] but insignificant. The lack of significance for international funds is surprising, considering the findings of Greene and Hodges (2002) and Zitzewitz (2003), whose analysis of market-timing trading implies a negative relationship between flow volatility and performance. However, it is consistent with the smaller number of international equity funds than domestic equity or bond funds in the sample, and the fact that international equity funds exhibit more noisy observations of the variables included in the tests. Overall, this suggests that the effect of flow volatility is not due simply to the marketing-timing trades of international funds.

TABLE 6

Cross-Sectional Regression Analysis by Fund Type

Table 6 presents the results of OLS regressions explaining cross-sectional differences in performance for the sample of 4,772 open-end mutual funds partitioned by investment objective. Here, α is the intercept from a daily 3-factor model of fund i's returns; SD_FLOW is the standard deviation of daily percentage flows; expense ratios are decomposed into 12B_1 and NON_12B_1 fees; SIZE is the natural log of average daily total net assets. * and ** indicate significance at the 5% and 1% levels, respectively. HAC (White (1980)) t-statistics are given in parentheses. The model is

$$(2) \qquad \alpha_i = \beta_0 + \beta_1 \text{SD\_FLOW}_i + \beta_2 \text{MEAN\_FLOW}_i + \beta_3 \text{SIZE}_i + \beta_4 \text{FRONT}_i + \beta_5 \text{DEFER}_i + \beta_6 \text{12B\_1}_i + \beta_7 \text{NON\_12B\_1}_i + \beta_8 \text{TURNOVER}_i + \beta_9 \text{CASH}_i + e_i.$$

Independent Variables	Domestic Equity Funds		Domestic Bond Funds		International Equity Funds	
Intercept	0.0022 (1.28)	0.0022 (1.27)	0.0338** (30.15)	0.0338** (30.25)	–0.0155 (–1.88)	–0.0156 (–1.88)
SD_FLOW	–0.0188** (–2.61)		–0.0014 (–0.49)		–0.0365 (–0.94)	
UNEXPECTED_ DAILY_FLOWS		–0.0173* (–2.57)		–0.0010 (–0.40)		–0.0320 (–0.89)
MEAN_FLOW	0.4562* (2.38)	0.4301* (2.44)	0.0460 (0.82)	0.0372 (0.79)	0.9148 (0.79)	0.8324 (0.76)
SIZE	0.0006** (2.83)	0.0006** (2.80)	–0.0008** (–6.01)	–0.0004** (–6.00)	0.0017 (1.82)	0.0017 (1.82)
DEFER	–0.0342 (–1.24)	–0.0347 (–1.25)	0.0729** (4.37)	0.0728** (4.36)	–0.1769 (–1.78)	–0.1774 (–1.79)
FRONT	–0.0330* (–2.10)	–0.0330* (–2.10)	0.0611** (6.17)	0.0611** (6.12)	–0.0120 (–0.23)	–0.0134 (–0.26)
12B_1	–0.3579** (–2.88)	–0.3547** (–2.85)	–0.6242** (–8.11)	–0.6233** (–8.06)	0.6285 (1.62)	0.6284 (1.62)
NON_12B_1	0.5291** (3.80)	0.5279** (3.79)	–0.8560** (–7.10)	–0.8562** (–7.10)	0.7955 (1.79)	0.7932 (1.78)
TURNOVER	–0.0035** (–4.52)	–0.0035** (–4.53)	–0.0004** (–3.17)	–0.0004** (–3.11)	–0.0043 (–1.53)	–0.0043 (–1.53)
CASH	–0.0002 (–0.04)	0.0001 (0.04)	–0.0209** (–3.97)	0.0212** (–3.88)	0.0662** (2.90)	0.0672** (2.94)
R^2	6.6%	6.5%	20.5%	20.5%	4.8%	4.6%

From the descriptive statistics presented in Table 5, the means of most variables for domestic equity funds fall in between those of domestic bond funds

[4]The use of alternative performance measures, such as using international equity and bond indices in the computation of α, do yield significant negative coefficient estimates (not reported) for flow volatility and unexpected flows.

and international equity funds. However, domestic equity funds do exhibit lower raw returns and higher 12b-1 fees and deferred loads than either domestic bond funds or international equity funds. This is consistent with higher marketing expenditures leading to changes in flows that could then have a detrimental impact on performance. Such a conjecture follows from the work of Jain and Wu (2000), who document that marketing effort does impact flows, while not being positively related to future returns.

VIII. Conclusions

This paper documents a significant negative relationship between daily mutual fund flow volatility and performance. A nearly identical relationship is documented between unexpected daily flows and performance. The negative relationship between fund flow volatility and performance is strongest for domestic equity funds.

The fact that flow volatility remains significant after correcting for funds' turnover suggests that it is not simply the increased trading by fund managers that drives the link between flow volatility and performance. The evidence here is consistent with the short-term discretionary trading of fund mangers, proxied for by turnover, being positively related to performance for equity funds, after correcting for its correlation with other variables. Short-term liquidity-motivated trading, proxied for by daily flow volatility and unexpected flows, is negatively related to performance.

The results of this study indicate that trading by fund investors plays an important role in determining cross-sectional differences in fund performance. The findings do not suggest that high portfolio turnover is the result of excessive trading, or "churning" by fund managers, but that it is the response to erratic daily flows from fund investors. It seems that there are more complex factors driving differences in performance across funds than previous studies have indicated, and that although flow-induced transaction costs are important, more research is needed to better understand the precise interaction between fund flows and fund managers' trading, as well as how far this interaction goes in explaining the unresolved issues regarding mutual fund performance.

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