What Drives the "Smart-Money" Effect?

Evidence from Investors' Money Flow to Mutual Fund Classes☆

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October 2016

Forthcoming *Journal of Empirical Finance*

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We wish to thank an anonymous referee, Laura Cardella, Filippo Curti, Jennifer Huang, Hayden Kane, Chris Lamoureux, John Nofsinger, Clemens Sialm, Rick Sias, Laura Starks, Harry Turtle, Huanhuan Zheng, and seminar participants at the Chinese University of Hong Kong, the Five-Star Forum at Renmin University of China, the University of Arizona, Washington State University for helpful comments and suggestions. The usual disclaimer applies.

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Abstract

The literature proposes two competing explanations — the "smart-money" and "persistent-flow" hypotheses — for the positive relation between mutual fund flow and future fund performance. We examine the flow-performance relation for different classes of U.S. domestic equity mutual funds. Our results show a stronger positive relation for the retail class than for the institutional class. More importantly, the significant relation for the retail class is mainly driven by funds with net outflow. This evidence is inconsistent with the smart-money hypothesis. We further show that retail funds exhibit greater persistence than institutional funds in net outflow. Once we control for expected fund flows, the flow-performance relation is no longer significant. We also perform robustness checks based on international funds and bond funds. The findings are supportive of the persistent-flow explanation.

Keywords: Fund flows; Smart-money effect; Persistent-flow explanation; Institutional funds; Retail funds; Fund classes

JEL classification: G10, G11, G14, G23

I. Introduction

The literature documents a significantly positive relation between mutual fund flow and future fund performance. For instance, using a sample of 227 stock mutual funds during the period of 1985-1994, Gruber (1996) finds that mutual fund flow positively predicts subsequent fund performance. That is, mutual funds with net inflow outperform those with net outflow. Similarly, Zheng (1999) confirms the positive relation between fund flow and performance. Both studies attribute this relation to the “smart-money” effect, namely, the ability of mutual fund investors to predict short-term fund performance and invest accordingly by moving money from poor performers to good ones. Although Sapp and Tiwari (2004) present evidence that the results documented in Gruber (1996) and Zheng (1999) are driven by stock return momentum, a recent study by Keswani and Stolin (2008) further confirms the significant positive relation between fund flow and subsequent fund performance based on monthly flows of U.S. mutual funds over more recent sample period of 1991-2004.

A number of studies have proposed an alternative explanation for the positive flow-performance relation based on the persistence of fund flows, which we refer to as the “persistent-flow” hypothesis. For instance, Wermers (2003) finds that investor flow-related buying pushes up stock prices beyond the effect of stock return momentum. He further shows that fund performance owes more to flow-related trades than to managers’ skill. Similarly, Lou (2012) argues that because fund flows are highly persistent, mutual funds with past inflows (outflows) are expected to receive additional capital (redemptions), expand (liquidate) their existing holdings, and drive up (down) their own performance in subsequent periods. Unlike the smart-money hypothesis, which attributes the positive relation between fund flow and future fund performance to investors’ ability to identify skilled fund managers, the persistent-flow hypothesis suggests a simple mechanism of price pressure — investors' flows to mutual funds drive this positive relation.

In this paper, we shed new light on what drives this positive flow-performance relation. We examine the flow-performance relation for different fund classes and provide evidence to distinguish the smart-money hypothesis versus persistent-flow hypothesis. Our study is motivated by the fact that actively managed mutual funds serve different investor clientele, including both institutional and retail investors. As documented in previous studies, institutional investors are sophisticated and have better understanding of fund characteristics (Del Guercio and Tkac, 2002; Keswani and Stolin, 2008; Evans and Fahlenbrach, 2012; Akbas, Armstrong, Sorescu, and Subrahmanyam, 2015). In contrast, retail investors are known to exhibit various behavioral biases, such as the disposition effect (Odean, 1998), or chasing funds based on past performance (Bailey, Kumar, and Ng, 2011). As such, if the positive flow-performance relation is driven by smart money, we expect it to be more pronounced among institutional funds. Moreover, as documented in Nanda, Wang and Zheng (2009), the market for retail mutual funds becomes highly segmented in the 1990s in terms of load and fee structures. For example, investors of front-end load and back-end load classes tend to be those who value professional financial advice and pay brokers and advisors to select funds on their behalf. On the other hand, investors of no-load classes are likely those who self-manage their portfolios and engage in active investment strategies. Thus, investors of no-load fund classes may exhibit stronger behavioral biases. Again, if the positive flow-performance relation is driven by smart money, we expect it to be more pronounced among load classes.

Our sample includes all actively managed U.S. domestic equity mutual funds in the CRSP (Center for Research in Security Prices) Survivor-Bias Free U.S. Mutual Fund Database. To have sufficient observations of institutional funds, our sample period starts from 1993 to 2014. We also restrict our sample to funds with valid observations of monthly total net assets (TNA) in order to obtain monthly fund flows.

Our main results show that for the full sample of U.S. domestic equity mutual funds, there is a significantly positive relation between fund flow and subsequent fund performance. That is, funds with net inflow outperform those with net outflow over the next month. We also observe that across different fund classes, there are substantial variations in the flow-performance relation. For example, although the fund flow predicts subsequent fund performance for both institutional and retail funds, the relation is stronger for retail funds, particularly no-load retail class. We note that certain funds offer multiple classes, including retail and institutional classes as well as load and no-load classes. Although these classes have different fee structures, they share the same underlying investment portfolio. As documented in Borgers, Derwall, Koedijk, and ter Horst (2016), the presence of institutional investors may affect portfolio holdings as well as fund performance. To perform our analysis in a cleaner setting, we follow Evans and Fahlenbrach (2012) to classify pure institutional funds and pure retail funds when a fund offers either institutional or retail class but not both. The results based on pure institutional and retail funds confirm that the positive flow-performance relation is stronger for retail funds than for institutional funds. From the perspective of smart-money hypothesis, these findings are puzzling. If the positive flow-performance relation is driven by the smart money of mutual fund investors, we expect the relation to be stronger among funds with more sophisticated investors, such as institutional funds.

Moreover, our empirical results reveal an important pattern, i.e., the significantly positive flow-performance relations are driven mostly by funds with net outflows. For instance, for retail funds, the monthly Carhart (1997) four-factor alpha and Cremers, Petajisto, and Zitzewitz (2013) four-factor alpha are, respectively, -0.076% and -0.019% for funds with positive flows and -0.149%

and -0.112% for funds with negative flows. The abnormal returns of funds with negative flows are of large magnitude and are significant at the 5% level based on both alphas. As such, the differences in performance between funds with positive and negative flows are also significant. In contrast, for institutional funds, the monthly Carhart (1997) four-factor alpha and Cremers, Petajisto, and Zitzewitz (2013) four-factor alpha are, respectively, -0.066% and -0.003% for funds with positive flows and -0.105% and -0.058% for funds with negative flows. The abnormal returns of funds with negative flows are of smaller magnitude relative to retail funds. As a result, the differences in performance are insignificant between funds with positive and negative flows. This pattern casts further doubt on the smart-money hypothesis. According to the smart-money hypothesis, investors should have the ability to identify not only the poor performers but also the good performers.

As robustness checks, we also examine the flow-performance relation for international funds and bond funds. If the positive flow-performance relation is driven by the smart money of mutual fund investors, we expect this relation to be stronger among funds with more sophisticated investors, such as bond funds. In contrast, our results show that there is a significantly positive flow-performance relation for international funds, but no evidence of a significant flow-performance relation for bond funds. Also, similar to the results for U.S. domestic equity mutual funds, the significantly positive flow-performance relation for international funds is driven mostly by funds with net outflow. For instance, the flow-weighted portfolio of funds with net outflow has a significantly negative four-factor alpha for retail international funds but an insignificantly negative four-factor alpha for institutional international funds. As such, the differences in performance between funds with positive and negative flows are significant for retail funds but insignificant for institutional funds.

To investigate further whether fund managers' skill may contribute to the positive flow-performance relation, we examine the relation between fund flow and active fund management. The main premise is that in response to net inflows, a skilled manager is more likely to expand investment opportunity by actively trading instead of passively trading on existing positions. A growing literature shows that active style is indicative of fund managers' superior skills. Using fund return R^2 (Amihud and Goyenko, 2013), active share (Cremers and Petajisto, 2009; Petajisto, 2013), and tracking errors as proxies for active style, our results show that fund flows are positively related to active style for institutional funds but not for retail funds. This is evidence that although institutional fund investors show an ability to pick active funds, there is no evidence of such ability among retail fund investors.

Finally, we explore the alternative explanation of the positive flow-performance relation, namely the persistent-flow hypothesis. Consistent with prior studies, we find that mutual fund flows are highly persistent. Moreover, we show that retail funds exhibit stronger persistence in net outflow than institutional funds. That is, retail investors tend to redeem their positions from mutual funds in a more persistent manner. Furthermore, as Coval and Stafford (2007) and Lou (2012), we decompose fund flow into expected and unexpected components. According to the persistent-flow hypothesis, if the positive relation between fund flow and subsequent performance is driven by flow-induced trades, then the unexpected component of fund flows should not have the predictive power of future fund performance. Our results show that unexpected fund flows indeed lack predictive power of future fund returns. In a multivariate setting, our results confirm that once we control for expected fund flows, total fund flow no longer has a significantly positive relation with future fund performance, evidence that the predictive power of fund flow for future fund performance is driven by the expected component. These findings are supportive of the persistent-flow hypothesis.

Our paper contributes to the mutual fund literature by shedding new light on a contentiously debated issue, i.e., whether mutual fund investors have the ability to identify funds with superior skills. Although studies by Gruber (1996) and Zheng (1999) interpret the positive fund flow-performance relation as evidence of smart money, Wermers (2003) and Lou (2012) propose an alternative explanation based on flow persistence. That is, the positive flow-performance relation is driven by the simple price impact of fund flows on stocks held in fund portfolios. In this paper, we examine investor flows to different classes of mutual funds and provide evidence to distinguish the smart-money hypothesis from the persistent-flow hypothesis. The results of our analyses based on U.S. domestic equity funds, as well as international funds and bond funds, provide evidence inconsistent with the smart-money hypothesis but supportive of the persistent-flow hypothesis.

The rest of the paper is organized as follows. Section II describes mutual fund data and our methodology. Section III presents main results, with further analysis performed in Section IV. Concluding remarks are included in Section V.

II. Data and Methodology

A. Mutual Fund Sample

The data used in this study is obtained from the CRSP Survivor-Bias Free US Mutual Fund Database. Our sample includes all open-end domestic equity funds in the database from January 1993 to December 2014. As Gruber (1996), Zheng (1999), and Sapp and Tiwari (2004), we exclude international funds, sector funds, specialized funds, and balanced funds to focus on actively managed U.S. equity mutual funds. To compute monthly fund flows, we further require a fund to have observations on monthly total net assets (TNA). Although the CRSP database has monthly TNA for mutual funds since 1991, it contains relatively few institutional funds before 1993. Thus, our sample period starts from January 1993. In our analysis, a fund entity is defined based on shares or classes. We divide mutual funds in our sample into institutional funds and retail funds.[1] Based on load and fee structure, we further classify retail funds into load and no-load classes.[2] Appendixes A and B provide details of the classification procedure. We perform robustness checks to ensure that our main results are robust to variations in fund classifications.

Table I reports summary statistics for the mutual fund sample. For each fund characteristic, we report the time series averages of cross-sectional means and medians. As shown in Table I, there are more retail funds than institutional funds in our sample. The average number of mutual funds per month in our sample is 3,355, with an average of 592 institutional funds and 2,763 retail funds per month. Average size, as measured by TNA, is $649.58 million. Retail funds on average are much larger than institutional funds, and among retail funds, the load class is largest. The average portfolio turnover ratio is 77.58%. Fund turnover ratio is defined as the minimum of aggregated sales or purchases of securities, divided by the 12-month TNA of the fund. Retail funds on average have a higher turnover ratio (80.00%) than institutional funds (72.32%). Among retail funds, the load class has an average turnover ratio of 80.56%; the no-load class turnover ratio is slightly lower at 79.42%. The average expense ratio of all funds in our sample is 1.33%. As

[1] The main criteria used by the CRSP database to classify funds as retail funds or institutional funds are the minimum investment requirement and the distributional channel of fund shares. For example, Morningstar classifies funds with a minimum initial investment requirement of $100,000 as institutional (see, e.g., James and Karceski, 2006).

[2] These fund classes are also referred to as Class A, B, and C, respectively. Reid and Rea (2003) and Nanda, Wang and Zheng (2009) provide an excellent review and discussion of the institutional background of the introduction of multiple-class shares. Briefly, investors of class A shares are subject to a front-end load fee but relatively low expense ratios. Investors of class B shares are subject to a back-end load fee or the so-called contingent deferred sales load (CDSL) and a higher expense ratio than class A. Usually, class B shares are automatically converted to class A shares if investors stay with the fund for more than six to eight years. Investors of class C shares are subject to no-load (or in some cases 1% back-end load if redeemed in the first year) but high expense ratios. Net returns to investors depend on the investment horizon. Reid and Rea (2003) show that class C shares (no-load) deliver better returns for investors with a one- to six-year investment horizon, class A shares (front-end load) dominate the other two classes for investors with investment horizons of more than eight years.

expected, institutional funds have lower expense ratios at 0.95%, compared with the 1.40% charged by retail funds. For retail funds with multiple classes, no-load class has an expense ratio of 1.60%, higher than the 1.46% for load class. Table I also shows that there is on average a positive monthly net flow for mutual funds in our sample. The average dollar amount of monthly flow is higher for institutional funds than for retail funds. This is mainly driven by the growth of institutional funds during our sample period. Among the retail funds, the no-load class has a higher dollar amount of monthly flow, reflecting the rapid growth of this class during our sample period. Finally, although the average fund return is 0.80% per month, the Carhart (1997) four-factor alpha (α^{4F}) is -0.07% for the whole sample of mutual funds. In addition, we note that institutional funds have a higher net return and α^{4F} than retail funds. This difference in return is mainly because retail funds charge a higher expense ratio.

B. Monthly Flow and Performance Measures

To examine the flow-performance relation, we form positive and negative flow portfolios based on fund flows in the previous month. Following Sirri and Tufano (1998), Chevalier and Ellison (1997), Gruber (1996), Zheng (1999), Sapp and Tiwari (2004), and Lou (2012), we compute investors' net flow to fund *i* during month *t* as follows:

$$Flow_{i,t} = TNA_{i,t} - TNA_{i,t-1} \times \left(1 + r_{i,t}\right) - MGTNA_{i,t} \tag{1}$$

where $TNA_{i,t}$ and $TNA_{i,t-1}$ refer to the total net asset (*TNA*) of fund *i* at the end of the month *t* and *t-1*, respectively. An implicit assumption in Eq. (1) is that new money flow to a fund is invested at the end of the month. Using the observed fund flow data of U.K. mutual funds, Keswani and Stolin (2008) show that the approximation of flow at a monthly frequency does not bias the inference on the flow-performance relation. $MGTNA_{i,t}$ is the increase in *TNA* due to mergers in month *t*.

Using the monthly flow for each fund, we form positive and negative flow portfolios based on whether the net flow of a fund is positive or negative during the previous month. We employ the "follow the money" approach of Elton, Gruber and Blake (1996) and Gruber (1996) to deal with merged funds. This approach assumes that investors in merged funds put their money in the surviving fund and continue to earn the return on the surviving fund. This approach also helps to mitigate the survivorship bias.

Each month, returns are computed for both equal- and flow-weighted portfolios. Unlike equal-weighted portfolios, flow-weighted portfolios emphasize those funds that experience the largest absolute investor flows. To evaluate the performance of the positive and negative flow portfolios, we use both the Fama and French (1993) three-factor model and the Carhart (1997) four-factor model. The Carhart (1997) four-factor model is specified as follows:

$$r_{p,t} = \alpha_p^{4F} + \beta_{1,p} MKTRF_t + \beta_{2,p} SMB_t + \beta_{3,p} HML_t + \beta_{4,p} UMD_t + \varepsilon_p \tag{2}$$

where $r_{p,t}$ is the monthly return on a portfolio of funds in excess of the one-month Treasury bill rate; *MKTRF* is the excess return on a value-weighted market portfolio; *SMB*, *HML*, and *UMD* are, respectively, returns on the zero-investment factor-mimicking portfolios for size, book-to-market, and momentum. The Fama and French (1993) three-factor model does not include the momentum factor.

As noted in Berk and van Binsbergen (2015), the benchmark portfolios in a factor model are artificial indexes. Consequently, abnormal performance based on these indexes might not capture the true ability of fund investors. An alternative way to examine the performance of positive and negative flow portfolios is to compare them with factors constructed from common and easily tradable benchmark indices. Thus, we also use the model of Cremers, Petajisto, and Zitzewitz (2013) to measure abnormal returns:

$$r_{p,t} = \alpha_p^{CPZ-4F} + \beta_{1,p} r_t^{S\&P500} + \beta_{2,p} r_t^{Russell2000-S\&P500} + \beta_{3,p} r_t^{Russell3000\ (Value-Growth)} + \beta_{4,p} UMD_t + \varepsilon_p \quad (3)$$

where the factors include the excess return on the S&P 500 index, the return on the Russell 2000 index minus the return on the S&P 500 index, the return on the Russell 3000 Value Index minus the return on the Russell 3000 Growth Index, and the Carhart (1997) stock return momentum (*UMD*).[3]

III. Main Analysis: Flow and Performance Relation

A. Performance of Flow Portfolios: Evidence Based on the Full Sample

Examining quarterly investors' money flows, Gruber (1996) and Zheng (1999) show that investors are able to earn superior returns based on their investment decisions. That is, funds that receive greater investor flow subsequently outperform their less popular peers. In this section, we examine the fund flow and performance relation for the full sample of mutual funds during the period of 1993-2014. Unlike the above studies, the monthly *TNA*s allow us to compute monthly fund flows. The evidence presented in Keswani and Stolin (2008) and Clifford, Jordan, and Riley (2014) suggests that the flow-performance relation is stronger at monthly frequency.

Panel A of Table II reports the performance of positive and negative fund flow portfolios for all funds and the differences in alphas between positive and negative flow portfolios. As described in Section II.B., alphas are based on the Fama-French three-factor alpha (α^{3F}) and Carhart's (1997) four-factor alpha (α^{4F}) as well as the Cremers, Petajisto, and Zitzewitz (2013) three-factor alpha (α^{CPZ-3F}) and four-factor alpha (α^{CPZ-4F}).

[3] We thank Martin Cremers, Antti Petajisto, and Eric Zitzewitz for data on the index-based factor returns for performance evaluation. We obtain the data from Antti Petajisto's website (http://www.petajisto.net/data.html).

The results in Panel A of Table II show that for the entire sample of mutual funds, the difference in α^{3F} between positive and negative flow portfolios is 0.129% (0.239%) per month for equal- (flow-) weighted portfolios. The differences are significant at the 1% level. This finding is consistent with Gruber (1996) and Zheng (1999). Sapp and Tiwari (2004) argue that if investors are indeed able to identify superior managers, then new fund flows should continue to earn positive abnormal returns even after controlling for the momentum factor. On the other hand, if fund investors merely chase funds based on past performance, then funds that happen to hold high concentration of recent winner stocks would receive on average more inflows of investor money. It also happens that these funds would benefit more than other funds from the effect of stock return momentum. In turn, this could lead to the finding of a positive flow-performance relation despite the absence of any ability by investors to select superior fund managers. The results based on α^{4F} in Panel A show that once the momentum factor is included in the performance benchmark, the differences in alpha between positive and negative flow portfolios, although still positive, reduce drastically for both the equal- and flow-weighted portfolios. The difference in α^{4F} becomes 0.069% (0.127%) per month for equal- (flow-) weighted portfolios and is significant only at the 10% level. Similar patterns are observed based on α^{CPZ-3F} and α^{CPZ-4F}. Finally, as shown in Panel A of Table II, the Sharpe ratio for positive flow portfolios is higher than for the negative flow portfolios. For example, equal- (flow-) weighted positive flow portfolios have a Sharpe ratio of 0.131 (0.136) compared with a Sharpe ratio of 0.107 (0.095) for the negative flow portfolios. The differences are significant at the 10% level.

The results show that based on monthly flows of actively managed U.S. equity funds over recent sample period from 1993 to 2014, there is a significantly positive flow-performance relation.

The results hold for both the equal- and flow-weighted portfolios, even after accounting for the momentum factor.

B. Performance of Flow Portfolios: Institutional Funds vs. Retail Funds

Actively managed mutual funds serve different clientele, including both institutional and retail investors. During our sample period, the number of institutional funds increased to 987 in 2014 from 31 in 1993. Consistent with James and Karceski (2006), the average size of institutional funds increased from $269 million in 1993 to $465 million in 2014. As documented in previous studies, retail investors differ substantially from institutional investors in investment objectives, financial background, and more importantly, their level of sophistication in terms of evaluating fund managers and selecting funds (e.g., Bergstresser, Chalmers, and Tufano, 2009; Nanda, Wang, and Zheng, 2009; Del Guercio, Reuter, and Tkac, 2010; Christoffersen, Evans, and Musto, 2013; Christoffersen and Simutin, 2012; Del Guercio and Reuter, 2014; Sialm and Starks, 2012; Sialm, Starks, and Zhang, 2015). Institutional investors are regarded as more sophisticated than their counterparts in retail funds (Del Guercio and Tkac, 2002; Keswani and Stolin, 2008; Evans and Fahlenbrach, 2012; Akbas, Armstrong, Sorescu, and Subrahmanyam, 2015). Moreover, retail investors have been documented as having various behavioral biases, such as the disposition effect and also chasing funds based on past performance (Odean, 1998), Bailey, Kumar, and Ng, 2011). To examine the flow-performance relation across different groups of mutual fund investors, we divide our sample of mutual funds into institutional funds versus retail funds.

Panels B and C of Table II report the performance of positive and negative fund flow portfolios for institutional and retail fund investors and also the differences in alphas between the positive and negative flow portfolios. If institutional investors benefit from their informational advantage and use more sophisticated evaluation procedures in picking fund managers, we expect money flows of institutional investors to have a stronger predictive power of subsequent fund performance. Panel B of Table II shows that for both equal- and flow-weighted institutional fund portfolios, the differences in α^{3F} and α^{CPZ-3F} between positive and negative flow portfolios is significant at the 5% and 1% levels, respectively. However, once we control for the momentum factor, the differences in α^{4F} and α^{CPZ-4F} between the positive and negative flow portfolios remain significant only for the flow-weighted portfolios.

The results in Panel C of Table II show that for retail funds, the differences in both α^{3F} and α^{CPZ-3F} between the positive and negative flow portfolios are positive and significant for both equal- and flow-weighted portfolios. Although controlling for the momentum factor reduces the difference in abnormal returns between the positive and negative flow portfolios, the differences in α^{4F} and α^{CPZ-4F} remain positive and significant for both equal- and flow-weighted portfolios. Specifically, the difference in α^{4F} between equal- (flow-) weighted positive and negative flow portfolios is 0.073% (0.126%) per month. Note that as reported in Table I, the average expense ratio for retail funds is about 1.40% per year. This suggests that the difference in α^{4F} between positive and negative flow portfolios is also of economic significance in the context of mutual fund investment.

Panels D and E of Table II also report the performance of flow portfolios formed for the samples of the load and no-load retail classes. As documented in Nanda, Wang and Zheng (2009), the market for retail mutual funds becomes highly segmented in the 1990s in terms of load and fee structures. For example, investors of both the front-end and back-end load classes tend to be those who value professional financial advice and pay brokers and advisors to select funds on their behalf. On the other hand, investors of the no-load class of funds are likely to be those who self-manage their portfolios and pursue active investment strategies. As a result, the relation between fund flow and future performance might vary across different retail fund investors.[4] Based on α^{3F} and α^{CPZ-3F}, funds with positive flow outperform those with negative flow for both the load and no-load classes (Panel D and Panel E). However, after controlling for the momentum factor, we find that the differences in α^{4F} and α^{CPZ-4F} are no longer significant for the load class of funds. In contrast, panel E illustrates that for the no-load class, the differences in α^{4F} and α^{CPZ-4F} remain positive and highly significant. These results hold for both equal- and flow-weighted portfolios.

By dividing mutual funds into various subsamples, the results in Table II show substantial variations in the flow-performance relation not only between institutional and retail funds, but also among different classes of retail funds. We note that although the results show a significant and robust relation between fund flow and performance for certain fund subsamples, it presents evidence inconsistent with the prediction of the smart-money hypothesis. As argued earlier, if the flow-performance relation is driven by smart money, we expect the relation to be stronger among funds with more sophisticated investors, such as institutional investors. Instead, the results show a stronger positive flow-performance relation for retail funds and especially for the no-load class of retail funds. We perform further analysis in Section IV to disentangle the smart-money hypothesis versus persistent-flow hypothesis.

C. Multivariate Test

[4] Bergstresser, Chalmers, and Tufano (2009) and Christoffersen, Evans, and Musto (2013) show that relative to direct-sold funds, broker-sold funds deliver lower risk adjusted returns. Del Guercio and Reuter (2014) further show that fund flows of investors in the segment of direct-sold funds are more responsive to risk-adjusted returns, which, in turn, gives direct-sold funds a stronger incentive to generate alpha than broker-sold funds.

In this section, we extend our earlier analysis and examine the flow-performance relation in a multivariate framework. Specifically, we perform panel regressions of fund returns on investors' flows and other fund characteristics. Following the literature, we also control for various fund characteristics that are potential determinants of subsequent fund performance. Specifically, for each month *t*, we estimate the following regression:

$$\hat{\alpha}_{i,t}^{4F} = Intercept_{i,t} + \beta_1 Flow_{i,t-1} + \beta_2 \log(TNA)_{i,t-1} + \beta_3 \alpha_{i,t-1}^{4F} + \beta_4 Expense\ Ratio_{i,t-1}$$
$$+\beta_5 Turnover_{i,t-1} + \beta_6 \log(Family\ Size)_{i,t-1} + \beta_7 Load_{i,t-1} + \varepsilon_{i,t} \qquad (4)$$

where the dependent variable, $\hat{\alpha}_t^{4F}$, is obtained as the fund excess return in month *t* less the sum of the products of each of the four-factor realizations and corresponding factor loadings. Fund factor loadings are estimated from the Carhart (1997) four-factor model based on the preceding 36 monthly fund returns. $Flow_{t-1}$ denotes lagged normalized monthly flow. $\log(TNA)_{t-1}$ is the logarithm of lagged fund total net asset (TNA). α_{t-1}^{4F} is the lagged fund alpha in month $t-1$, $Expense\ Ratio_{t-1}$, $Turnover_{t-1}$, $\log(Family\ Size)_{t-1}$, and $Load_{t-1}$ are, respectively, lagged expense ratio, turnover, the logarithm of family size, and maximum front-end and back-end load. These variables have been included in regression analysis in previous studies (e.g., Gruber, 1996; Chen, Hong, Huang, and Kubik, 2004; Chen, Yao, and Yu; 2007; Friesen and Sapp, 2007; Keswani and Stolin, 2008; Bergstresser, Chalmers, and Tufano, 2009; Huang, Sialm, and Zhang, 2011; and Sialm, Starks, and Zhang, 2015). In the regression, we also control for both time (month) and style fixed effects. Fund styles are classified as Size×Value based on a fund's rolling 36-month four-factor loadings. The standard errors are clustered by both time and fund.

Table III reports the regression results for the whole sample of funds, institutional funds, retail funds, and different classes of retail funds. The coefficients of other fund characteristics are similar to those reported in the literature. For example, smaller funds, funds that belong in a larger fund family, and funds with lower expenses tend to have higher returns. More importantly, the results for specification (1) confirm the positive relation between fund flow and future fund performance for the full sample of funds. Further, consistent with our portfolio results, the coefficient of fund flows is significant for institutional funds at the 10% level in specification (2) and for retail funds at the 5% level in specification (3). When we classify retail funds into the load and no-load classes (specifications (4) and (5)), we find that the positive relation between fund flows and performance is only significant for the no-load class.

D. Performance of Flow Portfolios: Pure Institutional Funds vs. Pure Retail Funds

Although different share classes vary in sales charges and fee structures for targeted investor clientele, they share the same underlying portfolio. Previous studies show that the presence of institutional investors may affect portfolio holdings as well as fund performance. For example, Borgers, Derwall, Koedijk, and ter Horst (2016) show that funds' exposures to socially sensitive stocks are weaker for funds that target institutional investors than for those that solely target retail investors. In this section, we perform robustness checks of our main findings based on pure institutional and pure retail funds. As in Evans and Fahlenbrach (2012), funds that only offer institutional classes are classified as pure institutional funds; similarly, funds that only offer retail classes are classified as pure retail funds.

Table IV reports the performance of positive and negative fund flow portfolios for pure institutional funds (Panel A), pure retail funds (Panel B) and for the load (Panel C) and no-load classes of pure retail funds (Panel D). Similar to results in Table II, for Panels A through E of Table IV, the differences in both α^{3F} and α^{CPZ-3F} between positive and negative flow portfolios are positive and significant for both equal- and flow-weighted portfolios. However, once we control for the momentum factor, the differences in α^{4F} and α^{CPZ-4F} between positive and negative fund flow portfolios, as reported in in Panel A, are no longer significant at any conventional level for pure institutional funds. In contrast, the differences in α^{4F} and α^{CPZ-4F} between positive and negative flow portfolios, as reported in Panel B, mostly remain significant for pure retail funds. The only exception is the difference in α^{4F} for equal-weighted portfolios. More importantly, once again, Table IV shows that the positive flow-performance relation is stronger for the no-load class of retail funds. The differences in α^{4F} and α^{CPZ-4F} between positive and negative fund flow portfolios, as reported in Panel D, are positive and significant for both equal- and flow-weighted portfolios for the no-load class of retail funds.

Similar to our analysis in Section III.C, we also perform multivariate tests for the samples of pure institutional and pure retail funds. The results are reported in Panel A of Table V and confirm the main findings in Section III.C. Namely, although the coefficient of flow is not significant for pure institutional funds in specification (1), we find a significantly positive relation between flow and subsequent performance for pure retail funds in specification (2). As presented in specification (4), the positive flow-performance relation is stronger for the no-load class of retail funds.

A recent study by Evans and Fahlenbrach (2012) finds that retail funds with an institutional twin outperform other retail funds. They use separate institutional investors account and identify twin retail and institutional funds based on the manager, investment objectives, fund families, and gross return correlations. Evans and Fahlenbarch (2012) argue that their finding is consistent with the reduction of the agency problem due to the monitoring role of institutional investors. However, they show that the positive effect of the presence of an institutional twin on fund performance does not extend to the sample of funds that offer both institutional and retail classes. We examine the effect of the presence of dual fund classes on the flow-performance relation. A dummy variable

($Dual$) is set equal to 1 if a fund offers both institutional and retail classes and zero otherwise. The results of the multivariate regressions are reported in Panel B of Table V. The results show that the only significant effect of dual fund classes is return persistence, i.e., the returns of funds with both institutional and retail classes are less persistent. More importantly, from specification (1) through (4), the coefficient estimates of both the dummy variable $Dual$ and the interaction between $Dual$ and *Flow* are statistically insignificant. That is, there is no evidence of a significant dual class effect on the flow-performance relation.

E. Performance of Flow Portfolios: Evidence Based on International Funds

The results in the previous section show significant fund flow-performance relations for actively managed U.S. domestic equity funds. In this section, we extend our analysis for actively managed international equity funds. The data are obtained from the CRSP Survivor-Bias Free U.S. Mutual Fund Database. International mutual funds are defined as those funds invested mainly in foreign equity markets.[5] We compute fund flows as in Eq. (1). Based on a monthly fund flow for each fund, we form positive and negative flow portfolios based on the net flow of a fund during the previous month. To evaluate the performance of positive and negative flow portfolios, we use the following specification:

$$r_{p,t} = \alpha_p + \beta_{1,p} MKTRF_t^{US} + \beta_{2,p} MKTRF_t^{Intl} + \beta_{3,p} SMB_t + \beta_{4,p} HML_t + \beta_{5,p} UMD_t + \varepsilon_{pt} \quad (5)$$

where $r_{p,t}$ is the monthly return on a portfolio of international funds in excess of the one-month Treasury bill (T-bill) rate. $MKTRF^{US}$ is the U.S. stock market return in excess of the one-month T-

[5] We select funds in the CRSP Survivor-Bias Free U.S. Mutual Fund Database with the following CRSP objective codes: EFRC, EFRQ, EFRM, EFRE, EFRI, EFRJ, EFRL, EFRP, EFRX, EFCL, EFCM, EFCS, EFCI, EFYG, EFYT

bill rate and is included to control for potential home bias.[6] Including $MKTRF^{US}$ marginally improves the explanatory powers of the factor model. For example, for the full sample of international funds, adjusted R^2 increases from 0.747 to 0.796 for positive flow portfolios and from 0.767 to 0.816 for negative flow portfolios. $MKTRF^{Intl}$ is the return on a value-weighted international market portfolio, excluding the U.S. market, in excess of the one-month T-bill rate; *SMB*, *HML*, and *UMD* are, respectively, returns on zero-investment factor-mimicking international portfolios for size, book-to-market, and momentum. The Fama and French (1993) international three-factor model does not include the international momentum factor.[7]

Table VI reports the performance of positive and negative flow portfolios for all international funds, institutional funds, and retail funds. Based on load and fee structures, we further classify international retail funds as either the load or no-load classes. The results are reported in Panels A and B, respectively, for both equal- and flow-weighted portfolios. As shown in Table VI, the difference in α^{3F} between positive and negative flow portfolios is highly significant for the full sample of international funds. However, in contrast to the results for domestic mutual funds, adding the global momentum factor has little impact on either the magnitude or the significance of the difference in performance between positive and negative flow portfolios. Specifically, even after controlling for the global momentum factor, funds with positive flows significantly outperform those with negative flows. The results hold for both equal- and flow-weighted portfolios.

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[6] We wish to thank the referee for the suggestion of including factors to control for potential domestic and equity bias in the analyses of international funds and bond funds.

[7] We obtain the Fama/French international three factors and international momentum factor from Kenneth R. French's website. Construction of the international factors is similar to the U.S. factors. The factors are based on 22 developed markets (excluding the U.S.). For more detailed information about the construction of the international factors, please visit (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library)

Comparing institutional funds versus retail funds, Table VI shows that the significant difference in α^{4F} between positive and negative flow portfolios is larger for retail funds. For retail funds, this difference is positive and significant at the 1% level. On the other hand, we find no significant difference in α^{4F} between positive and negative flow portfolios of institutional funds. Moreover, we find significant differences in α^{4F} between positive and negative flow portfolios for both the load and no-load classes of retail funds. Overall, these results mirror the findings based on U.S. domestic equity funds. Namely, there are clear variations in the flow-performance relation across different groups of international funds and the relation is stronger for retail funds than for institutional funds.

F. Performance of Flow Portfolios: Evidence Based on Bond Funds

We next investigate the flow-performance relation for bond funds. We focus on funds that invest in corporate bonds. Again, the data are obtained from the CRSP Survivor-Bias Free U.S. Mutual Fund Database.[8] Bond fund investors are generally considered more sophisticated than equity fund investors. If the positive flow-performance relation is driven by smart money, we expect the relation to be stronger for bond funds. To evaluate the performance of positive and negative flow portfolios, we follow previous studies (Blake, Elton, and Gruber, 1993; Boney, Comer, and Kelly, 2009; Ayadi and Kryzanowski, 2011), and use the following model:

$$r_{p,t} = \alpha_p^{BOND} + \beta_{1,p} MKTRF_t^{Bond} + \beta_{2,p} MKTRF_t^{Equity} + \beta_{3,p} DEFAULT_t + \beta_{4,p} TERM + \varepsilon_{pt} \quad (6)$$

where $r_{p,t}$ is the monthly return on a portfolio of funds in excess of the one-month T-bill rate; $MKTRF^{Bond}$ is the Vanguard Total Bond Market Index return in excess of the one-month T-bill rate. $MKTRF^{Equity}$ is the U.S. equity market return in excess of the one-month T-bill rate and is included

[8] We select funds with the following CRSP objective codes: ICQH, ICQM, ICQY, ICDS, ICDI, and IC.

to control for potential equity market bias. Including $MKTRF^{Equity}$ clearly improves the explanatory powers of the factor model. For example, for the full sample of bond funds, inclusion of $MKTRF_t^{Equity}$ increases adjusted R^2 to 0.596 from 0.405 for positive flow portfolios and to 0.691 from 0.398 for negative flow portfolios. *DEFAULT* is the difference in return between investment grade corporate bonds and government bonds (10-year Treasury Constant Maturity Yield); *TERM* is the difference in return between long-term (30-year Treasury Constant Maturity Yield) and short-term government bonds (one-year Treasury Constant Maturity Yield). We obtain the return for Vanguard Total Bond Market Index (Ticker = VBMFX) from Yahoo Finance. The rates for investment grade corporate bonds and for long- and short-term government bond rates are from the Federal Reserve's website.[9]

Table VII reports the performance of positive and negative flow portfolios for all bond funds, institutional funds, and retail funds as well as for the load and no-load classes of retail funds. The results are reported in Panel A and B, respectively, for both equal- and flow-weighted portfolios. The results in Table VII show no evidence of a significant flow-performance relation for the full sample of bond funds or for any subsample. That is, bond funds with net inflow do not outperform or underperform those with net outflow. Overall, the results are consistent with evidence documented in the literature. For instance, Chen, Ferson, and Peters (2010) and Cici and Gibson (2012) find no evidence of security selection or market timing abilities for bond funds.

IV. Further Analysis

[9] http://www.federalreserve.gov/releases/h15/data.htm

The results in the previous section suggest clear variations in the relation between fund flow and future performance for different funds or fund classes. Nevertheless, we observe two patterns throughout the empirical findings in the preceding section. Both challenge the smart-money hypothesis. First, our results show that based on U.S. domestic equity funds, the positive flow-performance relation is stronger for retail funds than for institutional funds and within retail funds, stronger for the no-load than the load class. Similar patterns are observed based on international funds. Nevertheless, we find no evidence of a significant positive flow-performance relation for bond funds. From the perspective of the smart-money hypothesis, these findings are puzzling. If smart money accounts for the positive flow-performance relation, we expect a stronger relation among funds with more sophisticated investors, such as institutional funds and bond funds. Second and more importantly, in all subsamples of funds with a significantly positive relation between fund flow and future performance, the difference in fund performance is driven mostly by the poor performance of funds with net outflow. For instance, for U.S. domestic retail funds, the monthly Carhart (1997) four-factor alpha and Cremers, Petajisto, and Zitzewitz (2013) four-factor alpha, as reported in Table II, are, respectively, -0.076% and -0.019% for funds with positive flows and -0.149% and -0.112% for funds with negative flows. The abnormal returns of funds with negative flows are significant at the 5% level based on both alphas. As such, the differences in performance are also significant between funds with positive and negative flows. In contrast, for U.S. domestic institutional funds, the monthly Carhart (1997) four-factor alpha and Cremers, Petajisto, and Zitzewitz (2013) four-factor alpha are, respectively, -0.066% and -0.003% for funds with positive flows and -0.105% and -0.058% for funds with negative flows. The differences in performance between funds with positive and negative flows are insignificant based on both alphas. Similar patterns are observed for international funds. For international retail funds, the monthly flow-weighted four-factor alpha is -0.021% for funds with positive flows and -0.393% for funds with negative flows. The abnormal return of funds with negative flows is significant at the 5% level. As a result, the difference in performance between funds with positive and negative flows is highly significant. In contrast, for international institutional funds, the monthly flow-weighted four-factor alpha is -0.190% for funds with positive flows and -0.289% for funds with negative flows. The difference in performance between funds with positive and negative flows is of a smaller magnitude and insignificant. These findings cast further doubt on the smart-money hypothesis under which investors are expected to not only have the ability to run away from bad performers but also the ability to identify good funds with superior skills.

In this section, we first examine the relation between fund flows and fund active style to further rule out manager skill as a potential explanation of the positive flow-performance relation. Second, we explore the alternative explanation of the flow-performance relation and provide evidence to substantiate the persistent-flow hypothesis.

A. Fund Flow and Active Style

Several recent studies document that more active fund managers have superior ability. For example, Amihud and Goyenko (2013) find a strong association between future fund performance and R^2, which is obtained from a regression of fund returns on a multifactor benchmark model. Specifically, they document that lower R^2 predicts better performance. Similarly, Cremers and Petajisto (2009) and Petajisto (2013) show active fund management, as measured by the share of portfolio holdings that differ from the benchmark index holdings, is related positively to future fund performance. If fund investors have the ability to identify superior funds, we expect that they are more likely to move money into funds with more active styles. This is because in response to net inflows, a skilled manager is more likely to expand investment opportunity by engaging in active trading instead of passively trading on existing positions.

Table VIII reports the time series averages of cross-sectional means of fund activeness measures of positive and negative flow portfolios for institutional funds (Panel A), retail funds (Panel B), as well as the load (Panel C) and no-load classes of retail funds (Panel D). R^2 is the proportion of the fund return variation explained by the Carhart (1997) four-factor model over the next 12 months (from month $t + 1$ to $t + 12$). *Active Share* represents the share of portfolio holdings that differ from the benchmark index at month $t + 1$ (Cremers and Petajisto, 2009, Petajisto, 2013).[10] *Tracking Error* is the standard deviation of error terms obtained by regressing excess fund return on excess market return over the subsequent 12 months (from month $t + 1$ to $t + 12$). Table VIII also reports differences in fund active style between positive and negative flow portfolios.

The results in Panel A of Table VIII show that institutional fund investors exhibit some ability to pick active funds. Specifically, those with positive flows have higher active share and tracking error than funds with negative flows. On the other hand, results in Panel B of Table VIII show that for retail funds, the difference in R^2 between positive and negative flow portfolios is significantly positive. In addition, we find no significant relation between fund flows and active share or tracking error. Overall these results suggest that compared with institutional fund investors, retail fund investors have no ability to pick active funds. The results for the load and no-load classes of retail funds are generally consistent with those for the whole sample of retail funds. These results suggest that fund manager's skill or fund active style unlikely contributes to the positive relation between fund flow and future performance for retail funds.

[10] We thank Antti Petajisto for the data on active share of mutual funds. Data on active shares was obtained from Antti Petajisto's website (http://www.petajisto.net/data.html).

B. Persistence in Fund Flows: Institutional Funds vs. Retail Funds

Given that all evidence so far is inconsistent with the prediction of smart-money hypothesis, in this and subsequent sections we now explore the alternative explanation for the positive flow-performance relation. Wermers (2003) finds that even after controlling for momentum returns, investor flow-related buying pushes up stock prices. Further, he shows that fund performance is more related to flow-related trades than to managers' skill. In addition, Lou (2012) argues that high performing mutual funds attract relatively higher flows, which are then reinvested by managers into their existing positions. In turn, this drives up the fund's own performance. Similarly, mutual funds with poor performance tend to liquidate existing holdings to meet redemption. Price pressure from liquidation of recent losers drives down the performance of these funds. Consequently, mutual funds with past inflows outperform their peers with past outflows. In other words, the positive relation between fund flows and future fund performance is the result of price pressure from investor money flows.

In this section, we examine persistence in flows and compare flow persistence between retail and institutional funds, with a focus on negative flows. It is well documented that fund flows are highly persistent, strongly related to past performance and to other fund characteristics (Sirri and Tufano, 1998; Wermers, 2003; Coval and Stafford, 2007; Lou, 2012). Similar to Coval and Stafford (2007), we estimate the following panel regression model for fund flows:

$$Flow_{i,t} = \alpha_t + \beta_1 Flow_{i,t-1:t-3} + \beta_2 Flow_{i,t-4:t-6} + \beta_3 Flow_{i,t-7:t-12} + \beta_4 Return_{i,t-1:t-12}$$
$$+\beta_5 \log(TNA)_{i,t-1} + \beta_6 Expense\ Ratio_{i,t-1} + \beta_7 Turnover_{i,t-1} + \beta_8 \log(Family\ Size)_{i,t-1}$$
$$+\beta_9 Load_{i,t-1} + \beta_{10} Return\ Vol_{t-1} + \beta_{11} Flow\ Vol_{t-1} + \varepsilon_{i,t} \quad (7)$$

where the dependent variable $Flow_{i,t}$ is normalized fund flows; $Flow_{i,t-1:t-3}$ is lagged normalized flow between t – 1 and t – 3; $Flow_{t-4,t-6}$ is lagged normalized quarterly flow between t – 4 and t –

6; $Flow_{t-7,t-12}$ is lagged normalized 6-month flow between $t-7$ and $t-12$. $Return_{t-1,t-12}$ is lagged 12-month fund return. $\log(TNA)_{t-1}$ is the logarithm of lagged fund total net asset (TNA). $Expense\ Ratio_{t-1}$, $Turnover_{t-1}$, $\log(Family\ Size)_{t-1}$, and $Load_{t-1}$ are, respectively, lagged expense ratio, turnover, logarithm of family size, and maximum front-end and back-end load. *Flow* (*Return) Volatility* is lagged monthly flow (return) volatility, measured as the standard deviation of monthly flow (return) over the previous 12 months. In the regression, we control for both time (month) and style fixed effects. Fund styles are classified as Size×Value based on a fund's rolling 36-month four-factor loadings. The standard errors are clustered by time and by fund. Finally, Lou (2012) shows that mutual funds respond in different ways to capital inflows and outflows. Therefore, we conduct separate regressions for the positive and negative flow subsamples.

The results in Table IX show that fund flows exhibit strong persistence in both positive flow in specification (1) and negative flow in specification (2), as $Flow_{i,t-1:t-3}$ and $Flow_{t-4,t-6}$ are both highly significant and positively associated with $Flow_{i,t}$. Comparing positive and negative subsamples further reveals that flow persistence is stronger in negative flow subsamples. For example, although we find no significant association between $Flow_{i,t}$ and $Flow_{t-7,t-12}$ for positive flow subsamples, the coefficient of $Flow_{t-7,t-12}$ is positive and significant for negative flow subsamples in specification (2). Not surprisingly, past return ($Return_{t-1,t-12}$) is strongly related to $Flow_{i,t}$ (Sirri and Tufano, 1998; Coval and Stafford, 2007). However, this positive relation is stronger for positive flow subsample. This finding is consistent with an asymmetric relationship between mutual fund flows and past performance documented in the literature (Gruber, 1996; Chevalier and Ellison, 1997; Sirri and Tufano, 1998).

We next investigate whether the results differ across different groups of funds. Our earlier findings show that the positive relation between fund flows and future performance is particularly pronounced for retail funds. If persistent flow is the main cause for this positive flow-performance relation, then we expect stronger persistence in retail than in institutional funds. To test this conjecture, we interact the lagged flow variables with a retail fund dummy (Dum^{Retail}) in specifications (3) and (4). Indeed, we find that the coefficients of the interaction terms between Dum^{Retail} and both $Flow_{i,t-1:t-3}$ and $Flow_{t-4,t-6}$ are significant and positive. These results suggest that retail fund flows indeed exhibit stronger persistence. Moreover, relative to positive flow in specification (3), negative flows exhibit stronger persistence in specification (4). When we classify retail funds into the load and no-load classes, the results further show that the strong persistence in retail fund flow is mainly driven by the no-load class.

C. Performance of Unexpected Flow Portfolios

In this section, we test whether the positive flow-performance relation is due to investors' skill or due to flow-induced trades. Specifically, as Coval and Stafford (2007) and Lou (2012), we decompose fund flows into expected and unexpected components. If the positive relation between fund flows and subsequent performance is due to investors' ability to identify superior fund management, then we should observe that unexpected flows also predict subsequent fund performance. Similar to Coval and Stafford (2007) and Lou (2012), we compute expected flows ($E[Flow]$) as the fitted values using the panel regression in Eq. (7) separately for positive and negative flows. Because Table IX documents significant differences in flows across different groups of investors, we estimate the regression coefficients within different group of funds. We confirm that the results are robust if we use the regression coefficients from the whole sample. Unexpected flows are computed as the difference between flow and expected flow, $Flow_{i,t} - E[Flow_{i,t}]$. Then, similar to the procedure described in Section II.B., with monthly unexpected flow for each fund, we form positive and negative flow portfolios based on unexpected net flow during the previous month. Finally, we evaluate performance based on the Fama-French three-factor alpha (α^{3F}) and the Carhart (1997) four-factor alpha (α^{4F}), as well as the Cremers, Petajisto, and Zitzewitz (2012) three-factor alpha (α^{CPZ-3F}) and four-factor alpha (α^{CPZ-4F}).

Table X reports the performance of positive and negative flow portfolios formed within the sample of all funds (Panel A), institutional funds (Panel B), retail funds (Panel C), and the load (Panel D) and no-load class (Panel E) of retail funds. The differences in α^{3F} and α^{4F} between positive and negative flow portfolios are insignificant across all different groups of fund investors. In other words, unexpected flow does not predict subsequent fund performance. The results suggest that the significant difference in α^{4F} between positive and negative flow portfolios is driven by expected fund flows. In addition, these results hold for both equal- and flow-weighted portfolios. The results challenge the smart-money hypothesis but clearly support the persistent-flow hypothesis.

D. Multivariate Test: Smart-Money Hypothesis vs. Persistent-Flow Hypothesis

In this section, we conduct a horse race between fund flow ($Flow$) and expected component of fund flow ($E[Flow]$) in terms of their predictive power of future fund performance in a multivariate setting by controlling for other fund characteristics known to relate to future fund performance. Specifically, we include $E[Flow_{i,t-1}]$ in Eq. (4) and rerun the regression. Once again, if mutual fund investors are smart enough to distinguish between good and bad managers, as suggested by the smart-money hypothesis, we should expect the positive relation between $Flow_{t-1}$ and subsequent fund performance to remain significant even after controlling for $E[Flow_{i,t-1}]$. Alternatively, if the flow-persistent hypothesis is the main reason of the positive flow-performance relation, then we expect $E[Flow_{i,t-1}]$to subsume the predictive power of total flow ($Flow_{t-1}$).

Table XI reports the regression results for the whole sample of funds, institutional funds, retail funds, and different classes of retail funds. The results are consistent with those in Table X, i.e., $E[Flow_{i,t-1}]$ is a significant predictor of subsequent fund performance in all regression specifications. More importantly, compared with Table III, the predictive power of $Flow_{i,t-1}$ is subsumed by $E[Flow_{i,t-1}]$. After controlling for expected flows ($E[Flow_{i,t-1}]$), the magnitude of the coefficient estimate and its significance for past fund performance (α_{t-1}^{4F}) are also decreased in specifications (1) through (5). These results are consistent with Lou (2012). The results again provide evidence that the significant flow-performance relation documented in our study is inconsistent with the smart-money hypothesis and instead supports the persistent-flow hypothesis.

V. Conclusion

The literature documents a positive relation between fund flows and future fund performance but offers competing explanations. Gruber (1996) and Zheng (1999) interpret the predictive power of fund flows for future fund performance as evidence that investors have the ability to pick funds with superior managers. Wermers (2003) and Lou (2012) attribute such a positive relation to a simple mechanism of price pressure caused by fund flows. Specifically, Lou (2012) argues that because flows are highly persistent, mutual funds with past inflows (outflows) are expected to receive additional capital (redemptions), expand (liquidate) their existing holdings, and drive up (down) their own performance in the subsequent period. In this paper, we examine the flow-performance relation for different classes of mutual funds to better understand what drives the positive flow-performance relation.

Our results show that, for the entire sample of funds, there is a significantly positive relation between fund flows and subsequent fund performance. In addition, across different subsamples of fund investors, we find substantial variations in flow-performance relation not only between institutional and retail funds but also among different classes of retail funds. Our results show that the positive flow-performance relation is mainly driven by retail funds, particularly by the no-load class. More importantly, our results further reveal an important pattern: The positive flow-performance relation is driven mostly by the performance of funds with negative flows. Similar patterns are observed based on international funds. These findings present challenges to the smart-money hypothesis.

We further examine the alternative explanation of the positive flow-performance relation, i.e., the persistent-flow hypothesis. Consistent with prior studies, we find a strong level of persistence in fund flows. Moreover, relative to positive flows, the persistence is stronger in negative flows, especially for retail funds. Once we decompose fund flows into expected and unexpected components, our results show that unexpected flows do not predict subsequent fund performance. Finally, in a multivariate setting, we confirm that the predictive power of fund flow for future fund performance is subsumed by expected component. Overall, the evidence inconsistent with the prediction of the smart-money hypothesis; instead, it supports the persistent-flow hypothesis as an explanation for the positive flow-performance relation.

Appendix A. Sample Selection: Actively Managed Mutual Funds

Our sample includes actively managed domestic equity funds in the CRSP mutual fund database from January 1993 to December 2014. As Kacperczyk, Sialm, and Zheng (2008), etc., we exclude international, balanced, sector, bond, money market, and index funds, as well as funds not invested primarily in equity securities. For more details, please refer to Kacperczyk, Sialm, and Zheng (2008). To identify whether a fund is an international fund, in addition to using the classification in the CRSP mutual fund database, we also use the words *"international," "global," "emerging," "non-U.S.," "Europe,"* and similar variants. For index funds, we use words such as *"index," "idx," and "s&p."* For sector funds, we use names such as *"utility," "sector," "technol," "health," "real estate," "natural resources,"* and similar variants. Finally, because the reported objectives do not always accurately reflect the portfolio holdings of a mutual fund (Kacperczyk, Sialm, and Zheng, 2008), we exclude funds that, on average, hold less than 80% or more than 105% in stocks. Elton, Gruber, and Blake (2001) and Evans (2010) identify a form of survivor bias in the mutual fund database that tends to be stronger in smaller funds. To mitigate the issue, we exclude from our sample funds with total net assets (TNA) of less than $10 million. Robustness checks show that relaxing the above restrictions does not qualitatively change our main results. Our final sample contains 885,771 fund-month observations representing 8,609 distinct funds.

Appendix B. Fund Identification Based on Investor Clientele

We mainly use investor classification provided by the CRSP Mutual Fund Database to classify funds into *institutional funds* versus *retail funds*. Unfortunately, this variable has two major issues: First, this classification is unavailable before December 1999. Second, the investor classification provided by the CRSP Mutual Fund Database is not well populated even after December 1999. For example, 18.33% of the funds cannot be classified either as retail or institutional funds. To resolve this issue, we use the following procedure to classify funds as institutional and retail funds before December 1999. First, we backfill the CRSP investor classifications for those funds that are available in the database after December 1999. Second, for the remaining funds, we rely on a word search algorithm to classify a fund as either institutional fund or retail funds based on fund names. Specifically, we search for words such as *"institutional shares," "institutional class," "inst shares," "instl," and "inst class"* in fund names and classify those funds with these keywords in their names as *institutional funds*. Similarly, we use keywords or fragments: *"retail," "retail shares," and "retail class"* to identify *retail funds*. Nanda, Wang, and Zheng (2009) point out that some mutual funds have multiple class structures to accommodate retail investors, we also search for the words such as *"class a", "a shares," "class b," "b shares," "class c," and "c shares,"* and classify funds that contain any of these keywords as *retail funds*. Finally, for the remaining funds, we manually search fund names to identify investor clientele. This procedure helps us to identify single-class retail funds that do not contain any of the above keywords. Finally, funds whose investor base is unclear,— such as *"class t" "class y," "class n," "class r," "class s," "class t," "class z,"* etc. — are categorized as *others*. These funds are less than 2.1% of our entire sample.

We also examine the accuracy of the fund classification procedure described above. To do so, we apply the classification procedure to the mutual fund sample after December 1999 and compare our classifications with those provided by the CRSP database. The results show that our algorithm provides correct identification for 93% of funds, and the search algorithm overall does a reasonable job in identifying the investor clientele of mutual funds. In the remaining 7% of cases (62,017 fund-month observations), we manually check the names and historical fees and load structures for fund classification. As robustness checks, we drop these funds and repeat the empirical analysis. We confirm that the results are consistent with those reported in the paper.

Finally, we also classify *retail funds* into *front-end load funds*, *back-end load funds,* and *no-load funds* based on their load and fee structures. In particular, funds with front-end load or those with a contingency deferred sales load (CDSL) are classified as *Load Class Funds*. If funds do not charge either of these loads, they are classified as *No-Load Funds*. Our final sample contains 156,289 fund-month observations for *institutional funds* and 729,482 fund-month observations for *retail funds*.

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Table I. Descriptive Statistics of Fund Characteristics

The table reports the time series averages of cross-sectional means and medians of the characteristics of mutual funds in our sample. The sample includes all actively managed U.S. equity mutual funds from the CRSP Survivorship-Bias Free U.S. Mutual Fund Database. Funds in our sample are classified as *institutional funds* and *retail funds*. *Retail funds* are further classified as *load* and *no load* based on their loads and fee structures. *N* is the number of funds. TNA denotes the total net assets of a fund at the end of month *t*. *Turnover* is defined as the minimum aggregate purchases or sales of securities during the year, divided by the average *TNA*. *Expense ratio* is the percentage of total investment that shareholders pay for the fund's operating expenses. We also report expense ratios for funds with multiple shares. *Load Fee* is the maximum percent charges applied at the time of purchase or the maximum percent charges when withdrawing money from the fund. The monthly fund flow for fund *i* during month *t* is measured as $TNA_{i,t} - TNA_{i,t-1} \times \left(1 + r_{i,t}\right) - MGTNA_{i,t}$, where $r_{i,t}$ is the fund's return in month *t*, and $MGTNA_{i,t}$ is the increase in fund's *TNA* due to mergers during month *t*. *Normalized Monthly Fund Flow* is computed as monthly net fund flow divided by the beginning of the month *TNA*. *Monthly Return* is the fund's monthly return. *Monthly Alpha* is the alpha of the four-factor model: $r_{p,t} = \alpha_p^{4F} + \beta_{1,p}MKTRF_t + \beta_{2,p}SMB_t + \beta_{3,p}HML_t + \beta_{4,p}UMD_t + \varepsilon_{pt}$, which is estimated based on the preceding 36 monthly fund returns. The sample period is from January 1993 to December 2014.

	All Funds		Institutional Funds		Retail Funds		Load Retail Class		No Load Retail Class	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
N	3,355		592		2,763		1,125		1,638	
TNA ($ millions)	649.58	105.31	321.84	105.96	707.39	105.23	778.97	114.91	661.43	100.18
Turnover (%)	79.58	62.70	78.32	64.81	79.27	61.90	80.78	64.58	78.42	60.15
Expense Ratio (%)	1.33	1.25	0.95	0.93	1.40	1.33	1.45	1.38	1.34	1.25
Expense Ratio-Multiple Shares (%)					1.53	1.51	1.46	1.41	1.60	1.68
Monthly Flow ($ millions)	0.97	-0.03	1.46	0.21	0.57	-0.08	0.02	-0.23	0.90	-0.01
Normalized Monthly Flow (%)	1.03	-0.09	1.24	0.23	0.95	-0.16	0.70	-0.30	1.09	-0.06
Monthly Return (%)	0.80	0.77	0.84	0.81	0.79	0.76	0.77	0.74	0.81	0.78
Monthly Alpha (%)	-0.07	-0.08	-0.04	-0.05	-0.07	-0.08	-0.09	-0.10	-0.06	-0.06

Table II. Performance of Fund Portfolios Formed on Past Flows

This table reports the average performance of positive and negative flow portfolios formed within the sample of all funds (Panel A), institutional funds (Panel B), and retail funds (Panel C). Each month, funds in each sample are grouped to form a positive and a negative fund flow portfolio based on the sign of the net fund flow of each fund during the previous month. Based on loads and fee structures, retail funds are further classified as *Load* (Panel D) and *No Load* (Panel E). Portfolio performance is evaluated based on portfolio alpha. The four-factor alpha (α^{4F}) is the intercept of the four-factor model: $r_{p,t} = \alpha_p^{4F} + \beta_{1,p}MKTRF_t + \beta_{2,p}SMB_t + \beta_{3,p}HML_t + \beta_{4,p}UMD_t + \varepsilon_{pt}$. The three-factor alpha (α^{3F}) is based on a model that excludes the momentum factor. Similarly, the CPZ four-factor alpha (α^{CPZ-4F}) is calculated from a factor model proposed by Cremers, Petajisto, and Zitzewitz (2013): $r_{p,t} = \alpha_p^{CPZ-4F} + \beta_{1,p}r_t^{S\&P500} + \beta_{2,p}r_t^{Russell2000-S\&P500} + \beta_{3,p}r_t^{Russell3000\ (Value-Growth)} + \beta_{4,p}UMD_t + \varepsilon_p$ which includes the excess return on the S&P 500 index and the returns on the Russell 2000 Index minus the return on the S&P 500 index, the Russell 3000 Value Index minus the return on the Russell 3000 Growth Index, and the momentum (UMD) factor. The CPZ three-factor alpha (α^{CPZ-3F}) is based on a model that excludes the momentum factor. The table reports estimates of alphas for equal-weighted and flow-weighted portfolios and the corresponding Sharpe ratios of the portfolios. The differences in alphas between the positive and the negative fund flow portfolios are also reported. Alphas are expressed in percentage per month. The statistical significance of alpha estimates are based on Newey–West standard errors. Statistical inferences for the differences in Sharpe ratios are based on the Jobson and Korkie Test. *, **, and *** , respectively, denote significance at the 10%, 5%, and 1% levels. The sample period is from January 1993 to December 2014.

	Equal-Weighted Portfolios					Flow-Weighted Portfolios				
	α^{3F}	α^{4F}	α^{CPZ-3F}	α^{CPZ-4F}	Sharpe Ratio	α^{3F}	α^{4F}	α^{CPZ-3F}	α^{CPZ-4F}	Sharpe Ratio
					Panel A: All Funds					
Positive Flow	-0.043	-0.076*	0.021	-0.018	0.131	0.026	-0.040	0.078	0.005	0.136
Negative Flow	-0.171***	-0.145**	-0.123**	-0.107**	0.107	-0.213***	-0.168***	-0.183***	-0.150**	0.095
Positive-Negative	0.129***	0.069*	0.145***	0.089**	0.024*	0.239**	0.127*	0.261***	0.154*	0.040*
					Panel B: Institutional Funds					
Positive Flow	-0.036	-0.066	0.032	-0.003	0.133	-0.009	-0.047	0.042	-0.003	0.134
Negative Flow	-0.118**	-0.105*	-0.061	-0.058	0.121	-0.166***	-0.144**	-0.115**	-0.106*	0.112
Positive-Negative	0.082**	0.039	0.093**	0.055	0.012	0.157***	0.097*	0.157***	0.103*	0.022

Panel C: Retail Funds										
Positive Flow	-0.042	-0.076*	0.020	-0.019	0.131	0.028	-0.041	0.078	0.002	0.1348
Negative Flow	-0.177***	-0.149**	-0.131**	-0.112**	0.105	-0.215***	-0.168***	-0.187***	-0.153**	0.0938
Positive-Negative	0.135***	0.073*	0.151***	0.093**	0.025*	0.243**	0.126*	0.265***	0.155*	0.041*
Panel D: Load Class Retail Funds										
Positive Flow	-0.064	-0.103**	-0.005	-0.049	0.124	-0.004	-0.076	0.041	-0.039	0.127
Negative Flow	-0.179***	-0.151***	-0.138***	-0.121**	0.104	-0.192***	-0.149**	-0.176***	-0.146**	0.096
Positive-Negative	0.115**	0.049	0.133**	0.071	0.021	0.189**	0.073	0.217**	0.108	0.032
Panel E: No-Load Class Retail Funds										
Positive Flow	-0.025	-0.057	0.040	0.002	0.135	0.050	-0.021	0.106	0.030	0.139
Negative Flow	-0.174***	-0.145**	-0.123**	-0.104**	0.107	-0.224***	-0.173**	-0.188***	-0.149**	0.094
Positive-Negative	0.149***	0.089**	0.163***	0.106**	0.028**	0.275**	0.152**	0.295***	0.178*	0.046*

Table III. Multivariate Tests: Regressions of Fund Performance on Fund Flows and Otl Attributes

This table reports the results of the panel regressions of actively managed mutual fund performance or previous month's fund flows and other fund characteristics. Fund performance is the monthly fund al estimate ($\hat{\alpha}_t^{4F}$), which is obtained as the fund excess return in month *t* less the sum of the products of e of the four-factor realizations and corresponding factor loadings. Fund factor loadings are estimated f the Carhart (1997) four-factor model based on the preceding 36 monthly fund returns. $Flow_{t-1}$ den lagged normalized monthly flow, $\log(TNA)_{t-1}$ is the logarithm of lagged fund total net asset (TNA). α is lagged fund alpha in month t-1, $Expense\ Ratio_{t-1}$, $Turnover_{t-1}$, $\log(Family\ Size)_{t-1}$, and $Load$ are, respectively, lagged expense ratio, turnover, logarithm of family size, and maximum front-end back-end load. Both time and style fixed-effects are controlled for in the regression. Fund styles classified as Size×Value based on a fund's rolling 36-month four-factor loadings. The t-statistics parentheses) are based on standard errors clustered by both fund and time. *, **, and *** , respectiv denote significance at the 10%, 5%, and 1% levels. The sample period is from January 1993 to Decen 2014.

	All Funds	Institutional Funds	Retail Funds	Retail Funds: Load Class	Retail Funds: No Load Cla
	(1)	(2)	(3)	(4)	(5)
$Flow_{t-1}$	0.400**	0.246*	0.456**	0.290	0.559**
	(2.05)	(1.68)	(2.02)	(1.05)	(2.55)
α_{t-1}^{4F}	0.158***	0.139**	0.161***	0.145**	0.172***
	(2.79)	(2.27)	(2.84)	(2.41)	(3.04)
$\log(TNA)_{t-1}$	-0.019**	-0.026***	-0.021**	-0.021*	-0.022**
	(-2.33)	(-3.54)	(-2.16)	(-1.68)	(-2.34)
$Expense\ Ratio_{t-1}$	-0.065***	-0.825**	-0.704***	-0.664***	-0.729***
	(-7.56)	(-3.91)	(-7.14)	(-5.11)	(-6.47)
$Turnover_{t-1}$	-0.023	-0.021	-0.023	-0.034	-0.016
	(-1.00)	(-0.74)	(-1.04)	(-1.30)	(-0.77)
$\log(Family\ Size)_{t-1}$	0.010**	-0.011	0.013*	0.026**	0.007*
	(2.10)	(-1.16)	(1.69)	(2.30)	(1.93)
$Load_{t-1}$	-0.188*		-0.278**	-0.818	
	(-1.70)		(-2.36)	(-1.32)	
$Intercept$	-0.189***	-0.185***	-0.186***	-0.196***	-0.145***
	(-3.98)	(-5.08)	(-3.85)	(-3.12)	(-4.08)
Time FE	Y	Y	Y	Y	Y
Style FE	Y	Y	Y	Y	Y
Clusters: Time and Fund	Y	Y	Y	Y	Y
N	654,071	115,817	538,254	234,970	303,284
R^2	0.109	0.123	0.107	0.109	0.106

Table IV. Performance of Fund Portfolios Formed on Past Flows: Pure Institutional and Pure Retail Funds

This table reports the average performance of positive and negative fund flow portfolios formed within the sample of pure institutional funds and pure retail funds. Pure institutional funds are classified as those that only have institutional classes in the funds (Panel A). Pure retail funds are classified as those that only have retail classes in the funds (Panel B). Based on loads and fee structures, pure retail funds are further grouped into Load (Panel C) and *N*o Load (Panel B). Each month, funds within each sample are grouped to form a positive flow portfolio and a negative flow portfolio based on the sign of the net flow of each fund during the previous month. Alphas are expressed in percentage per month. For definitions of other variables, please refer to Table II. Statistical significance of alpha estimates are based on Newey–West standard errors. Statistical inference for the differences in Sharpe ratios are based on the Jobson and Korkie Test. *, **, and *** , respectively, denote significance at the 10%, 5%, and 1% levels. The sample period is from January 1993 to December 2014.

	Equal-Weighted Portfolios					Flow-Weighted Portfolios				
	α^{3F}	α^{4F}	α^{CPZ-3F}	α^{CPZ-4F}	Sharpe Ratio	α^{3F}	α^{4F}	α^{CPZ-3F}	α^{CPZ-4F}	Sharpe Ratio
					Panel A: Pure Institutional Funds					
Positive Flow	0.017	-0.019	0.085	0.042	0.147	0.100	0.046	0.157*	0.092	0.161
Negative Flow	-0.075	-0.067	-0.009	-0.010	0.134	-0.065	-0.031	-0.006	0.015	0.138
Positive-Negative	0.093*	0.048	0.094*	0.051	0.013	0.165*	0.076	0.163	0.077	0.023
					Panel B: Pure Retail Funds					
Positive Flow	-0.026	-0.058	0.035	-0.004	0.134	0.057	-0.015	0.108	0.029	0.140
Negative Flow	-0.165***	-0.136**	-0.119**	-0.101*	0.108	-0.195***	-0.150**	-0.169**	-0.138**	0.097
Positive-Negative	0.139***	0.078*	0.154***	0.097**	0.026*	0.252**	0.135	0.277**	0.167*	0.043*
					Panel C: Load Class Pure Retail Funds					
Positive Flow	-0.059	-0.099**	-0.005	-0.052	0.124	0.046	-0.036	0.082	-0.007	0.132
Negative Flow	-0.169***	-0.139**	-0.131**	-0.113**	0.104	-0.133*	-0.092	-0.123*	-0.097	0.106
Positive-Negative	0.110**	0.040	0.126**	0.061	0.019	0.179*	0.055	0.205**	0.090	0.026
					Panel D: No-Load Class Pure Retail Funds					
Positive Flow	-0.007	-0.038	0.055	0.018	0.139	0.067	-0.006	0.123	0.044	0.142
Negative Flow	-0.161***	-0.132**	-0.111**	-0.092*	0.110	-0.222***	-0.171**	-0.188**	-0.150**	0.093
Positive-Negative	0.153***	0.094**	0.166***	0.110**	0.029**	0.289***	0.166*	0.311***	0.194*	0.049*

Table V. Multivariate Tests: Pure and Dual Class Funds

This table reports the results of the panel regressions of actively managed pure and dual mutual fund performance on the previous month's fund flows and other fund characteristics. Pure institutional (retail) funds are classified as those that only have institutional (retail) class in the funds in Panel A. Dual institutional (retail) funds are classified as those that have both institutional and retail classes in the funds in Panel B. Based on loads and fee structures, pure and dual retail funds are further grouped into load and no load classes. Fund performance is the monthly fund alpha estimate ($\hat{\alpha}_t^{4F}$), which is obtained as the fund excess return in month t less the sum of the products of each of the four-factor realizations and corresponding factor loadings. Fund factor loadings are estimated from the Carhart (1997) four-factor model based on the preceding 36 monthly fund returns. For definitions of other variables, please refer to Table III. In the regression both time and style fixed effects are controlled for. Fund styles are classified as Size×Value based on a fund's rolling 36-month four-factor loadings. The t-statistics (in parentheses) are based on standard errors clustered by both fund and time. *, **, and ***, respectively, denote significance at the 10%, 5%, and 1% levels. The sample period is from January 1993 to December 2014.

Panel A. Pure Institutional and Retail Funds

	Pure Institutional Funds	Pure Retail Funds	Pure Retail Funds	
			Load Class	No Load Class
	(1)	(2)	(3)	(4)
$Flow_{t-1}$	0.198	0.461**	0.209	0.621***
	(0.64)	(2.02)	(0.75)	(2.58)
α_{t-1}^{4F}	0.204***	0.194***	0.194***	0.193***
	(3.23)	(3.47)	(3.31)	(3.36)
$\log(TNA)_{t-1}$	-0.054***	-0.027**	-0.023	-0.030**
	(-2.62)	(-2.23)	(-1.45)	(-2.52)
$Expense\ Ratio_{t-1}$	-0.103**	-0.619***	-0.636***	-0.635***
	(-2.46)	(-4.92)	(-4.09)	(-4.43)
$Turnover_{t-1}$	0.006	-0.016	-0.023	-0.012
	(0.17)	(-0.79)	(-1.05)	(-0.60)
$\log(Family\ Size)_{t-1}$	-0.010	0.025***	0.042***	0.016*
	(-0.48)	(2.65)	(2.73)	(1.73)
$Load_{t-1}$		-0.365**	-1.127	
		(-2.31)	(-1.63)	
$Intercept$	0.237***	-0.202***	-0.180***	-0.165***
	(5.14)	(-4.86)	(-2.60)	(-3.94)
Time FE	Y	Y	Y	Y
Style FE	Y	Y	Y	Y
Clusters: Time and Fund	Y	Y	Y	Y
N	25,382	341,461	139,793	201,668
R^2	0.119	0.098	0.100	0.098

Panel B. The Effect of Dual Fund Class

	Institutional Funds	Retail Funds	Retail Funds	
			Load Class	No Load Class
	(1)	(2)	(3)	(4)
$Dual$	-0.015	-0.008	-0.007	-0.009
	(-0.37)	(-0.45)	(-0.26)	(-0.40)
$Flow_{t-1}$	0.291	0.503**	0.262	0.645***
	(0.94)	(2.15)	(0.93)	(2.67)
$Flow_{t-1} * Dual$	-0.038	-0.129	0.104	-0.258
	(-0.13)	(-0.59)	(0.33)	(-1.07)
α_{t-1}^{4F}	0.221***	0.197***	0.196***	0.194***
	(3.44)	(3.50)	(3.30)	(3.38)
$\alpha_{t-1}^{4F} * Dual$	-0.108*	-0.124***	-0.151***	-0.089*
	(-1.90)	(-2.97)	(-3.28)	(-1.89)
$\log(TNA)_{t-1}$	-0.051**	-0.023**	-0.015	-0.028**
	(-2.54)	(-1.97)	(-1.00)	(-2.42)
$\log(TNA)_{t-1} * Dual$	0.031	0.007	-0.006	0.014
	(1.46)	(0.61)	(-0.40)	(1.04)
$Expense\ Ratio_{t-1}$	-0.928**	-0.594***	-0.539***	-0.634***
	(-2.36)	(-4.60)	(-3.22)	(-4.38)
$Expense\ Ratio_{t-1} * Dual$	0.131	-0.202	-0307	-0.129
	(0.30)	(-1.26)	(-1.44)	(-0.75)
$Turnover_{t-1}$	-0.023	-0.025	-0.035	-0.018
	(-0.79)	(-1.07)	(-1.30)	(-0.83)
$\log(Family\ Size)_{t-1}$	-0.006	0.017**	0.028**	0.012*
	(-0.58)	(2.08)	(2.32)	(1.71)
$Load_{t-1}$		-0.237**	-0.731	
		(-1.96)	(-1.21)	
$Intercept$	-0.188***	-0.207***	-0.213***	-0.164***
	(-4.06)	(-4.22)	(-3.36)	(-4.40)
Time FE	Y	Y	Y	Y
Style FE	Y	Y	Y	Y
Clusters: Time and Fund	Y	Y	Y	Y
N	115,817	538,254	234,970	303,284
R^2	0.123	0.107	0.109	0.107

Table VI. Performance of Fund Flow Portfolios – International Funds

This table reports the performance of positive and negative flow portfolios formed within the samples of all international funds and institutional, and retail international funds. Based on loads and fee structures, retail funds are further classified as Load and No-Load. Each month, international mutual funds are grouped to form positive and negative flow portfolios based on the sign of the net fund flow of each fund during the previous month. Portfolio performance is evaluated based on portfolio alpha. The four-factor alpha is the intercept of four-factor model: $r_{p,t} = \alpha_p + \beta_{1,p} MKTRF_t^{US} + \beta_{2,p} MKTRF_t^{Intl} + \beta_{3,p} SMB_t + \beta_{4,p} HML_t + \beta_{5,p} UMD_t + \varepsilon_{pt}$. Factor portfolios are derived for international markets, excluding the United States. To accommodate home bias, the U.S. market return excess risk-free rate is also included. The three-factor alpha is based on a model that excludes the international momentum factor. The table reports estimates of alphas for equal-weighted (Panel A) and flow-weighted (Panel B) portfolios. The differences in alphas between the positive and the negative flow portfolios are also reported. Alphas are expressed in percentage per month. Statistical significance of alpha estimates is based on Newey–West standard errors. *, **, and ***, respectively, denote significance at the 10%, 5%, and 1% levels. The sample period is from January 1993 to December 2014.

	All Funds		Institutional Funds		Retail Funds		Load Retail Class		No Load Retail Class	
	α^{3F}	α^{4F}	α^{3F}	α^{4F}	α^{3F}	α^{4F}	α^{3F}	α^{4F}	α^{3F}	α^{4F}
Panel A. Equal-Weighted Portfolios										
Positive Flow	-0.085	-0.111	-0.151	-0.165	-0.072	-0.098	-0.076	-0.108	-0.068	-0.093
Negative Flow	-0.308*	-0.310*	-0.315*	-0.319*	-0.314*	-0.315*	-0.295*	-0.295*	-0.322*	-0.323*
Positive-Negative	0.223***	0.199***	0.072*	0.066	0.242***	0.216***	0.218***	0.187***	0.254***	0.230***
Panel B. Flow-Weighted Portfolios										
Positive Flow	-0.051	-0.086	-0.185	-0.208	-0.000	-0.036	-0.029	-0.036	0.020	-0.028
Negative Flow	-0.361**	-0.363**	-0.249	-0.248	-0.378**	-0.380**	-0.259*	-0.266*	-0.435**	-0.433**
Positive-Negative	0.310***	0.277***	0.064	0.040	0.378***	0.344***	0.230***	0.230***	0.455***	0.405***

Table VII. Performance of Fund Flow Portfolios – Bond Funds

This table reports the performance of positive and negative flow portfolios formed within the samples of all bond funds, institutional funds, and retail funds. Based on loads and fee structures, retail funds are further classified as Load and No Load. Each month, bond mutual funds are grouped to form positive and a negative fund flow portfolios based on the sign of the net fund flow of each fund during the previous month. Portfolio performance is evaluated based on portfolio alpha. The portfolio alpha (α^{Bond}) is the intercept of the following model: $r_{p,t} = \alpha_p^{BOND} + \beta_{1,p} MKTRF_t^{Bond} + \beta_{2,p} MKTRF_t^{Equity} + \beta_{3,p} DEFAULT_t + \beta_{4,p} TERM + \varepsilon_{pt}$, which includes the excess market return (RMRF), default risk (DEFAULT), and term risk (TERM). The excess return on the bond market ($MKTRF_t^{Bond}$) is the Vanguard Total Bond Market Index return excess risk-free rate, *DEFAULT* denotes the difference in return between investment grade corporate and government bonds (10-year Treasury Constant Maturity Yield); *TERM* is defined as the difference in return between long-term (10-year Treasury Constant Maturity Yield) and short-term government bonds (1-year Treasury Constant Maturity Yield). To accommodate equity bias, the CRSP value-weighted U.S. market return excess risk-free rate is also included ($MKTRF_t^{Equity}$). The table reports estimates of alphas for equal-weighted (Panel A) and flow-weighted (Panel B) portfolios. The differences in alphas between the positive and the negative flow portfolios are also reported. Alphas are expressed in percentage per month. Statistical significance of alpha estimates is based on Newey–West standard errors. *, **, and *** denote significance at the 10%, 5%, and 1% levels. The sample period is from January 1993 to December 2014.

	All Funds	Institutional Funds	Retail Funds	Retail Funds: Load Class	Retail Funds: No Load Class
	α^{Bond}	α^{Bond}	α^{Bond}	α^{Bond}	α^{Bond}
		Panel A. Equal-Weighted Portfolios			
Positive Flow	-0.038	-0.031	-0.041	-0.048	-0.038
Negative Flow	-0.029	-0.021	-0.033	-0.038	-0.028
Positive-Negative	-0.009	-0.010	-0.008	-0.011	-0.010
		Panel B. Flow-Weighted Portfolios			
Positive Flow	-0.054	-0.064	-0.037	-0.038	-0.038
Negative Flow	-0.022	-0.027	-0.019	-0.017	-0.034
Positive-Negative	-0.032	-0.037	-0.018	-0.021	-0.004

Table VIII. Fund Flow and Active Style

This table reports the time series averages of cross-sectional means of active style measures for positive and negative flow funds. The sample includes all actively managed U.S. equity mutual funds from the CRSP Survivorship-Bias Free U.S. Mutual Fund Database. Funds in our sample are classified as institutional funds and retail funds. Retail funds are further classified as load and no-load based on their loads and fee structures. R^2 is the proportion of the fund return variance that is explained by the variation in the four-factor model of Carhart (1997) over the subsequent 12 months (from month $t + 1$ to $t + 12$). *Active Share* represents the share of portfolio holdings that differ from the benchmark index at month $t + 1$ (Cremers and Petajisto, 2009). Tracking error is the standard deviation of error terms obtained by regressing excess fund return on excess market return over the subsequent 12 months (from month $t + 1$ to $t + 12$). The differences in active style between positive and negative flow portfolios are also reported. Statistical significance is based on Newey–West standard errors. *, **, and ***, respectively, denote significance at the 10%, 5%, and 1% levels. The sample period is from January 1993 to December 2014.

	Positive Flow	Negative Flow	Positive-Negative
	Mean	Mean	Mean
Panel A. Institutional Funds			
R^2	0.938	0.939	-0.001
Active Share	0.791	0.779	0.012**
Tracking Error (%)	0.017	0.016	0.001***
Panel B. Retail Funds			
R^2	0.929	0.924	0.005**
Active Share	0.801	0.795	0.006
Tracking Error (%)	0.017	0.017	-0.000
Panel C. Load Class Retail Funds			
R^2	0.929	0.926	0.003
Active Share	0.795	0.783	0.013
Tracking Error (%)	0.017	0.016	0.000
Panel D. No-Load Class Retail Funds			
R^2	0.928	0.922	0.005***
Active Share	0.807	0.806	0.001
Tracking Error (%)	0.017	0.017	-0.000

Table IX. Persistence of Fund Flows

This table reports the results of the panel regressions of mutual fund flows on lagged fund flows, lagged fund returns, and other fund characteristics. Each month, mutual fund flows are categorized into a positive and a negative fund flow based on the sign of the net fund flow of each fund during the current month. $Flow_{t-1,t-3}$ is lagged normalized quarterly flow between t – 1 and t – 3; $Flow_{t-4,t-6}$ is lagged normalized quarterly flow between t – 4 and t – 6; $Flow_{t-7,t-12}$ is lagged normalized six-month flow between t – 7 and t – 12. Dum^{Retail} ($Dum^{Load-Retail}$, $Dum^{No-Load-Retail}$) is a dummy variable that is 1 if fund is a retail fund (Load Class Retail Fund, No Load Class Retail Fund), zero otherwise. For definitions of other variables, please refer to Section 4.B. In the regression, both time and style fixed effects are controlled for. Fund styles are classified as Size×Value based on a fund's rolling 36-month four-factor loadings. The *t*-statistics (in parentheses) are based on standard errors clustered by both fund and time. *, **, and ***, respectively, denote significance at the 10%, 5%, and 1% levels. The sample period is from January 1993 to December 2014.

	Positive Flow (1)	Negative Flow (2)	Positive Flow (3)	Negative Flow (4)	Positive Flow (5)	Negative Flow (6)
Dum^{Retail}			-0.001*	0.003***		
			(-1.75)	(8.87)		
$Dum^{Load-Retail}$					0.008***	-0.004***
					(2.65)	(-3.27)
$Dum^{No-Load-Retail}$					-0.001*	0.002***
					(-1.91)	(8.40)
$Flow_{t-1,t-3}$	0.119***	0.045***	0.094***	0.037***	0.094***	0.037***
	(30.11)	(20.44)	(24.89)	(16.50)	(24.92)	(16.47)
$Flow_{t-1,t-3} * Dum^{Retail}$			0.033***	0.011***		
			(6.04)	(3.35)		
$Flow_{t-1,t-3} * Dum^{Load-Retail}$					0.035***	0.014***
					(5.32)	(3.39)
$Flow_{t-1,t-3} * Dum^{No-Load-Retail}$					0.032***	0.009***
					(5.38)	(2.67)
$Flow_{t-4,t-6}$	0.030***	0.016***	0.023***	0.013***	0.023***	0.013***
	(13.08)	(15.71)	(7.87)	(9.36)	(7.92)	(9.37)
$Flow_{t-4,t-6} * Dum^{Retail}$			0.009**	0.004**		
			(2.47)	(2.14)		
$Flow_{t-4,t-6} * Dum^{Load-Retail}$					0.008*	-0.002
					(1.80)	(-0.96)
$Flow_{t-4,t-6} * Dum^{No-Load-Retail}$					0.010**	0.011***
					(2.44)	(4.82)
$Flow_{t-7,t-12}$	-0.001	0.009***	0.001	0.009***	0.001	0.009***
	(-1.39)	(16.16)	(0.85)	(12.20)	(0.91)	(12.28)
$Flow_{t-7,t-12} * Dum^{Retail}$			-0.003**	0.000		
			(-2.45)	(0.37)		
$Flow_{t-7,t-12} * Dum^{Load-Retail}$					-0.004**	-0.001

					(-2.57)	(-1.33)
$Flow_{t-7,t-12}$ * $Dum^{No-Load-Retail}$					-0.003**	0.002**
					(-2.01)	(2.16)
$Return_{t-1,t-12}$	0.024***	0.013***	0.023***	0.013***	0.023***	0.013***
	(4.26)	(6.99)	(4.12)	(6.96)	(4.13)	(7.11)
$\log(TNA)_{t-1}$	-0.006***	0.002***	-0.006***	0.002***	-0.006***	0.002***
	(-23.89)	(12.18)	(-23.53)	(11.07)	(-23.54)	(10.45)
$Expenses_{t-1}$	-0.129***	-0.152***	-0.164***	-0.203***	-0.198***	-0.176***
	(-2.82)	(-6.03)	(-3.57)	(-8.15)	(-4.57)	(-7.14)
$Turnover_{t-1}$	0.004***	-0.001***	0.004***	-0.001***	0.004***	-0.001***
	(10.60)	(-7.82)	(10.45)	(-7.78)	(10.48)	(-8.04)
$\log(Fam\ Size)_{t-1}$	0.145***	-0.039*	0.147***	-0.042*	0.139***	-0.029
	(3.11)	(-1.84)	(3.18)	(-1.96)	(3.19)	(-1.44)
$Load_{t-1}$	-0.026***	0.025***	-0.030***	0.017***	-0.191***	0.152***
	(-3.77)	(6.62)	(-4.06)	(4.38)	(-3.55)	(6.69)
$Return\ Vol_{t-1}$	-0.004	-0.073***	-0.002	-0.071***	-0.001	-0.072***
	(-0.15)	(-6.84)	(-0.08)	(-6.73)	(-0.05)	(-6.80)
$Flow\ Vol_{t-1}$	0.144***	-0.117***	0.146***	-0.115***	0.145***	-0.115***
	(15.26)	(-30.72)	(15.22)	(-29.98)	(15.50)	(-30.77)
$Intercept$	0.014***	-0.013***	0.014***	-0.015***	0.014***	-0.015***
	(14.65)	(-31.74)	(15.57)	(-29.86)	(15.57)	(-31.24)
Time FE	Y	Y	Y	Y	Y	Y
Style FE	Y	Y	Y	Y	Y	Y
Clusters: Time and Fund	Y	Y	Y	Y	Y	Y
N	256,525	386,837	256,525	386,837	256,525	386,837
R^2	0.227	0.132	0.228	0.134	0.228	0.136

Table X. Performance of Fund Portfolios Formed on Unexpected Flows

This table reports the average performance of positive and negative flow portfolios formed within the samples of all funds (Panel A), institutional funds (Panel B), retail funds (Panel C). Each month, funds in each sample are grouped to form a positive and a negative flow portfolio based on the sign of the unexpected net fund flow of each fund during the previous month. Unexpected fund flow is defined as the difference between normalized monthly flow and expected fund flows, which is calculated as the fitted values by using the coefficient estimates in the panel regressions in Table VIII. Based on loads and fee structures, Retail Funds are further classified as Load Class (Panel D) and No Load Class (Panel E). Alphas are expressed in percentage per month. For definitions of other variables, please refer to Table II. Statistical significance of alpha estimates are based on Newey–West standard errors. Statistical inferences for the differences in Sharpe ratios are based on the Jobson and Korkie Test. *, **, and ***, respectively, denote significance at 10%, 5%, and 1% level. The sample period is from January 1993 to December 2014.

	Equal-Weighted Portfolios					Flow-Weighted Portfolios				
	α^{3F}	α^{4F}	α^{CPZ-3F}	α^{CPZ-4F}	Sharpe Ratio	α^{3F}	α^{4F}	α^{CPZ-3F}	α^{CPZ-4F}	Sharpe Ratio
					Panel A: All Funds					
Positive Flow	-0.104**	-0.092*	-0.051	-0.047	0.122	-0.078*	-0.058	-0.049	-0.038	0.122
Negative Flow	-0.110***	-0.124***	-0.053	-0.075	0.119	-0.094*	-0.135***	-0.047	-0.096	0.116
					Differences					
Positive-Negative	0.006	0.032	0.002	0.028	0.003	0.016	0.077	-0.001	0.058	0.006
					Panel B: Institutional Funds					
Positive Flow	-0.088	-0.073	-0.033	-0.025	0.127	-0.095*	-0.069	-0.057	-0.040	0.122
Negative Flow	-0.058	-0.095**	0.008	-0.035	0.130	-0.096	-0.139**	-0.035	-0.085	0.119
					Differences					
Positive-Negative	-0.030	0.022	-0.041	0.009	-0.003	0.002	0.070	-0.022	0.045	0.003
					Panel C: Retail Funds					
Positive Flow	-0.105**	-0.094*	-0.054	-0.050	0.121	-0.077*	-0.058	-0.049	-0.040	0.122
Negative Flow	-0.116***	-0.128***	-0.061	-0.080*	0.117	-0.094*	-0.134**	-0.048	-0.097	0.116
Differences					Differences					
Positive-Negative	0.012	0.034	0.007	0.030	0.004	0.017	0.077	-0.001	0.057	0.006

					Panel D: Load Class Retail Funds					
Positive Flow	-0.118**	-0.109**	-0.071	-0.071	0.117	-0.074	-0.055	-0.058	-0.051	0.120
Negative Flow	-0.125***	-0.137***	-0.074*	-0.093**	0.114	-0.092*	-0.125**	-0.048	-0.090	0.116
					Differences					
Positive-Negative	0.008	0.028	0.002	0.022	0.002	0.018	0.070	-0.010	0.039	0.004
					Panel E: No-Load Class Retail Funds					
Positive Flow	-0.092*	-0.079	-0.038	-0.032	0.125	-0.077*	-0.060	-0.041	-0.034	0.123
Negative Flow	-0.110**	-0.122***	-0.052	-0.071	0.120	-0.100*	-0.146***	-0.052	-0.107*	0.114
					Differences					
Positive-Negative	0.018	0.043	0.014	0.039	0.005	0.023	0.086	0.011	0.073	0.008

Table XI. Regressions of Fund Performance on Fund Flows, Expected Fund Flows, and Other Attributes

This table reports the results of the panel regressions of actively managed mutual fund performance on a previous month's fund flows, expected fund flows, and other fund characteristics. Fund performance is the monthly fund alpha estimate ($\hat{\alpha}_t^{4F}$), which is obtained as the fund's excess return in month *t* less the sum of the products of each of the four-factor realizations and corresponding factor loadings. Fund factor loadings are estimated from the Carhart (1997) four-factor model based on the preceding 36 monthly fund returns. $Flow_{t-1}$ denotes lagged normalized monthly flow, $E[Flow_{t-1}]$ denotes expected fund flows. $E[Flow_{t-1}]$ is calculated as the fitted values by using the coefficient estimates in the panel regressions in Table VIII. For definitions of other variables, please refer to Table III. The *t*-statistics (in parentheses) are based on standard errors clustered by both fund and time. *, **, and ***, respectively, denote significance at the 10%, 5%, and 1% levels. The sample period is from January 1993 to December 2014.

	All Funds	Institutional Funds	Retail Funds	Retail Funds	
				Load Class	No-load Class
	(1)	(2)	(3)	(4)	(5)
$Flow_{t-1}$	-0.218	-0.009	-0.280	-0.416	-0.205
	(-1.36)	(-0.07)	(-1.47)	(-1.61)	(-1.06)
$E[Flow_{t-1}]$	1.434***	0.711***	1.642***	1.537***	1.747***
	(4.25)	(2.77)	(4.34)	(3.64)	(4.70)
α_{t-1}^{4F}	0.117*	0.116*	0.113*	0.101	0.120*
	(1.87)	(1.83)	(1.89)	(1.63)	(1.95)
$\log(TNA)_{t-1}$	-0.016*	-0.026***	-0.018*	-0.017	-0.019*
	(-1.88)	(-3.54)	(-1.74)	(-1.32)	(-1.94)
$Expense\ Ratio_{t-1}$	-0.622***	-0.846***	-0.683***	-0.643***	-0.714***
	(-6.84)	(-4.00)	(-6.66)	(-4.77)	(-6.13)
$Turnover_{t-1}$	-0.024	-0.022	-0.024	-0.034	-0.017
	(-1.01)	(-0.75)	(-1.03)	(-1.28)	(-0.77)
$\log(Family\ Size)_{t-1}$	0.006*	-0.017	0.010*	0.024*	0.003
	(1.77)	(-1.63)	(1.71)	(1.91)	(0.34)
$Load_{t-1}$	-0.112		-0.221*	-1.000	
	(-0.99)		(-1.83)	(-1.60)	
$Intercept$	-0.206***	-0.192***	-0.202***	-0.191***	-0.150***
	(-4.24)	(-5.25)	(-4.11)	(-3.02)	(-3.21)
Time FE	Y	Y	Y	Y	Y
Style FE	Y	Y	Y	Y	Y
Clusters: Time and Fund	Y	Y	Y	Y	Y
N	651,066	115,168	535,898	234,429	301,469
R^2	0.109	0.123	0.107	0.109	0.107