Fund Flow and Return: Evidence from Individual Funds

Karen L. Benson

UQ Business School, University of Queensland, Brisbane

Robert W. Faff

Department of Accounting and Economics, Monash University, Melbourne

Tom Smith

School of Finance and Applied Statistics, Australian National University, Canberra.

Contact Author: Dr Karen Benson, UQ Business School, University of Queensland,
St Lucia. Qld. 4072. Australia.
k.benson@business.uq.edu.au
Telephone: +61 7 33654348

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Abstract

We assess the two-way relation between fund flows and fund returns at the individual fund level. We present new insights in the context of a simultaneous equation model capturing endogeneity and assessing the joint effects of current and past returns and flows. Our modeling accounts for variation in fund size, age and expenses; as well as business cycles and general market sentiment. We show that contemporaneous flows and returns have a key role to play in understanding the flow/performance linkage. Notably, we find that current flows have a negative impact on returns consistent with managers finding it difficult to quickly place large inflows of cash. In turn, current returns have a positive impact on flows showing that investors react quickly to performance information.

Key words: Mutual fund flows; mutual fund returns; endogeneity; contemporaneous linkage

1. Introduction

The Investment Act, 1940, requires mutual funds to calculate their fund share price daily, although the dissemination of these prices (e.g. through the media) is not mandatory. Despite the voluntary nature of revealing such information, reference to the financial press and to individual fund web-sites demonstrates that mutual fund prices are widely available on a very timely basis. This is particularly true in recent years with the dramatic growth and proliferation in electronic media and information technology. On the demand side, rational investors are expected to seek out and promptly react to this information – a sensitive barometer of their decisions should be the daily flow of new money into and out of individual funds. As a consequence of the likely sensitivity in money flows, we can characterize the scenarios facing managers into two cases: either they are required to place net new funds or to meet liquidity demands reflected by net money outflows. Both these activities will likely affect return in a speedy fashion. It follows that the relation between fund return and flows is both contemporaneous and endogenous. The contemporaneous linkage will be accentuated by the conventional use of the monthly sampling interval, given that many investors will be reacting to information over a much narrower timeframe than one month. The primary goal of our paper is to assess this contemporaneous relationship at the individual fund level. We test for, and find, an endogenous relationship between fund flow and fund return. After controlling for endogeneity, our key finding is that current flows have a significant negative impact on returns and, current returns have a significant positive effect on flows.

The lack of attention to the contemporaneous flow/returns relation is a serious gap in the literature. It is evident from the literature that the flow of funds, at the individual fund level, is a function of past performance (Chevalier and Ellsion,1997 and Sirri and Tuffano, 1998). Given the timely reporting of fund returns and performance measures we argue that flows are a function of current performance. Indeed, market timing activities, where investors move in and out of mutual funds to take advantage of short-term market moves and stale prices, shows that investors do obtain and act on daily fund prices. Chalmers, Edelen and Kadlec (2001) state that there are exploitable profit opportunities for mutual fund investors because the price of a fund is determined by valuing the underlying net assets using the last trade of these assets,. The last trade for an asset may be many hours before the market closes and, hence, does not reflect the most recent information. Therefore, there is some predictability in the next day fund prices which can be exploited by investors. Goetzmann, Ivkovic and Rouwenhorst (2001) identify the same profit opportunities in international funds. Greene and Hodges (2002) examine the daily flows from international funds and find that fund investors who actively trade in mutual funds, on the basis of stale prices, do dilute the returns of the funds.

In the assessment of factors that determine flows, there is little evidence testing the contemporaneous relation between flows and performance. One exception is Chevalier and Ellison (1997) who incorporate both lagged and current return as control variables. Their sampling interval is annual and they note that the significant coefficient on the current return shows investors do react to year to date performance. Similarly, Deaves (2004), using annual data, finds a significant effect of current return on fund flows. However, the use of annual data largely camouflages the contemporaneous effect that that we have in mind.

We account for the endogeneity between flows and performance and this is an additional contribution to the literature. The effect of performance on flows is an important issue to fund managers since the inflows/outflows impact on the growth of the fund and, hence, the compensation received by managers (Chevalier and Ellison, 1997). The growth of the fund is also a direct function of returns. To achieve high returns, fund managers need to maximize their stock selection abilities and/or market timing activities. However, the ability of the fund manager to be good selectors and market timers is also heavily influenced by the funds they are required to place or liquidate, that is, the flow of money to the fund. It would be difficult for a manager to immediately and optimally place a major inflow of newly contributed cash into 'core' assets; hence, the holding of such cash will result in the temporary 'parking' of the money, thereby leading to a depressed percentage return of the fund. Conversely, a large outflow of cash may accelerate the need for managers to liquidate assets to meet investor demand. The timing of such sales may induce otherwise inferior portfolio re-weightings, thereby reducing fund return. The increase in trade as a result of flows will result in lower fund returns (Edelen, 1999). Alternatively, if funds maintain a liquidity 'buffer' for such contingencies, then overall risk and very likely return will be dampened. Berk and Green (2004) state that investors competitively supply money to fund managers. The managers have decreasing returns to scale in applying their superior abilities to the generation of fund returns. Hence, returns are also a function of flows and this relationship may exist both contemporaneously and historically.

Our research focuses on the potential contemporaneous relation between flows and returns. This study addresses the interrelationship of these two key variables. We first test for and find an endogenous relationship between flows and returns. Then, using a simultaneous equation model capturing endogenous linkages, we show that the estimation of factors that drive returns and flows is best achieved by a joint assessment of these issues. We find significant relations between contemporaneous and past returns and flows. Specifically, current flows have a negative impact on returns whereas lagged flows have a positive impact. Current and lagged returns have a significant positive impact on flows. Our model controls for the variation in fund age, size, expenses and general market sentiment. The evidence shows that fund managers find it difficult to quickly place large inflows of cash or effectively deal with large requests for outflows. Investors are very quick to recognize the high performing funds and their money follows. The results are robust to different estimation methods and a series of relationships previously identified in the literature that impact on flows and returns. The direction of our contemporaneous relationships is maintained when we account for the asymmetry between past returns and past flows and alternate business cycles. We also find institutional fund flows are less sensitive to lagged return and the returns on new funds are less sensitive to past flows.

This paper is organized as follows. In Section 2 we provide a brief overview of the literature, Section 3 outlines the data and methods and Section 4 presents and discuses the results. A conclusion is provided in Section 5.

2. Brief Literature Review

A large body of the literature on fund return focuses on the performance evaluation of the fund. The underlying motivation of these studies is to assess if fund managers can add value relative to the market return and/or other relevant benchmarks. Various performance evaluation models are used. Early research focuses on the Jensen measure using a CAPM approach. More recently researchers have extended these models to include market timing variables (Treynor and Mazuy, 1966 and Henrikkson and Merton, 1981), Fama French factors (from Fama and French 1993), Fama French factors plus a momentum factor (Carhart, 1997), and lagged economic variables interacting with market returns reflected in a conditional asset pricing model (Ferson and Schadt, 1996). In general, funds as a group are unable to outperform the market although there is some limited evidence of abnormal performance at the individual level. Somewhat paradoxically, despite these sobering results, aggregate investment in mutual funds continues to grow. As a result there is a large segment of the literature that focuses on mutual fund flows, in the hope that it is the key to resolving the paradox.

We categorize our review of the literature on fund flows and performance into three areas. First we consider how, at the individual fund level, performance may drive fund flow and how other variables may affect this relation. Second, we consider the converse position and review studies that examine whether and to what extent individual fund flows impact on own-performance. Finally, we consider studies that adopt an aggregate market perspective on the flow/performance relation.

2.1 Fund flows as a function of fund performance at the individual fund level

Intuitively we would expect that investors will place their money with the funds that are currently performing well. Investors have information on past returns and in a competitive market it is expected that this information will be acted on in a timely fashion. Notably, there is overwhelming evidence of a convex flow/performance relation. Specifically, a good performance outcome will result in an increase in money inflow; however, poor performance does not necessarily result in a money outflow (Siri and Tufano, 1998). This asymmetric linkage is not consistent across all types of funds. Del Guicio and Tkac (2002) find that the asymmetry is evident for mutual funds but not pension funds. Other information available to investors and assessed in the fund literature includes age, fees, volatility of fund returns, participation costs, marketing, fund size, and group size. Various studies (see, for example, Santini and Aber, 1998; Huang, Wei and Yan, 2004) examine the impact of these variables on fund flows.

Given that past performance is an important factor in choosing an investment opportunity, the persistence of fund performance has also been examined in the literature (see, for example, Brown and Goetzmann, 1995; Elton, Gruber and Blake, 1996; Christopherson, Ferson and Glassman, 1998). Results are mixed however: persistence in poor performing funds is relatively consistent across studies but persistence in good performing funds is far less convincing. A puzzling question is why would investors continue to invest in funds that do not consistently do well? Lynch and Musto (2003) address this issue from an analytical perspective and argue that past performance provides information about manager skill. When a fund is performing badly the expectation is that there will be a strategy change, hence, poor past performance is not conveying information and as such is not relevant to fund flows.

Berk and Green (2004) propose that flows do follow performance and investors use the past information on performance in a rational manner. Their analytic model combines 3 elements: the competitive provision of capital by investors to mutual funds, differential ability of managers, and learning about managerial ability from past returns. The model assumes no asymmetric information and no moral hazard. They argue that money does flow to positive past performers supporting the flow/performance relation. However, the inflow of funds ensures future returns are competitive and excess returns cannot be maintained. The size of the funds is increasing, yet there is a decreasing return to size.

2.2 Performance as a function of fund flows at the individual fund level

The impact of fund flows on returns at the individual fund level has been assessed in a variety of ways. Zheng (1999) examines if new money flows can predict future returns, that is, do investors shift cash to value enhancing funds. The results generally show that funds which receive more money outperform those funds that lose money. However, the effect is relatively short lived, up to 30 months, and is more significant for smaller funds. The results can be attributed to fund specific factors and explained in general by investors choosing winning funds that repeat their performance. In contrast, Lamont and Frazzini (2005) find that investors tend to place money with funds that subsequently do poorly.

Ferson and Schadt (1996) hypothesise that betas are, *inter alia*, driven by the flow of money, that is, the larger the cash inflow the lower the fund beta. They regress the change in sales (new money) on the change in dividend yield lagged and change in T-bills lagged. Their results show that cash flows into the fund increase when public expectations of market returns increase and, hence, betas decrease. Edelen (1999) shows that liquidity motivated flows affect mutual fund returns. He regresses abnormal return on liquidity-motivated flows, information motivated flows and lagged abnormal return. Greene and Hodges (2002) consider if daily fund flows cause a shift in the cash balance of the fund resulting in a dilution impact. The implication is that active mutual fund traders who can accurately predict future returns of the fund's risky assets can benefit from trading strategies. The active fund trader receives the price swing in the fund assets, along with other investors, without a cost. The traders, with their cash inflow, are diluting short term positive returns to the passive investors. Their results show the dilution effect is relevant to international funds but not domestic funds.

2.3 Aggregate market flows

In the aggregate fund flow literature the main focus is on the relation between fund flows and market returns. Two key hypotheses are the price pressure hypothesis and the feedback trader hypothesis. The price pressure hypothesis assesses the affect mutual fund flows have on market returns and the information content of fund flows. Closely allied to this hypothesis is the impact of investor sentiment on returns. Warther (1995) finds evidence to support this hypothesis with his results showing that fund flows and security prices move together. Tests of the feedback trader hypothesis assess the affect security returns have on mutual fund flows. Warther's results do not support feedback trading as there is no positive relation between flows and lagged returns. Edelen and Warner (1999 and 2001) find a concurrent relation between flow and returns as well as evidence to support flows following market returns i.e. feedback trading. Fant (1999) separates flows into four components: new sales, redemptions, exchanges-in and exchanges-out where exchanges represent transfers between equity and non-equity funds. His results show evidence of feedback from returns to exchanges-out but no relation between returns and sales or redemptions. There is no support for the price pressure hypothesis.

The direction of causality has been examined in the context of aggregate flows and market returns. Granger causality tests are used by Fortune (1998), Edwards and Zhang (1998), Boyer and Zheng (2002), and Cha and Kim (2005). The results are mixed but in general there is Granger causality from stock market returns to aggregate fund flow but not from flows to returns. Goetzmann and Massa (2003) adopt a VAR model and a simultaneous equation model to examine the relationship between flows to index funds and the S&P 500 return. They test for the directional causality from flows to returns. Their results show a contemporaneous correlation between inflows and returns. There is evidence of negative but not positive feedback trading.

Market volatility is related to flows but high volatility does not result in an outflow of funds. Expert opinion and investor uncertainty also influence flows.

In summary, the aggregate market literature establishes a contemporaneous relation between aggregate fund flow and market return. The effect of aggregate flow on subsequent market returns (price pressure) is mixed. In contrast, the literature at the individual fund level can be clearly separated into studies that examine drivers of fund flows and drivers of performance. In general the results identify a lagged relationship. However, of importance is Edelen (1999) who examines the effect of fund flows on fund returns and recognises both the lagged and contemporaneous relation.

3. Experimental Framework

3.1 Base Case Model

Our model is designed to determine if the return of a given fund is a function of its own fund flows and if its fund flows are simultaneously a function of its own-fund returns. We examine this question in the context of both lagged and contemporaneous linkages. The relevance of market returns as a determining factor of fund return is recognised. Further we incorporate the return on the bond market, given that investors may shift between equities and bonds depending on relative market conditions. Fund flow is measured as total dollar flow following Fant and O'Neal (2000). We seek to examine the effect of flows, not the percentage change in the fund size.[1] We thus avoid the potential spurious relationship induced by scaling pointed out by Pearson (1897), Kronmal (1993) and Kim (1999).[2]

Included in the model are a number of conventional control variables which we select using the literature as guidance: size; age; and expenses. Size is important in the flow relationship as the larger funds are more likely to attract larger inflows – thus, fund size will

[1] Fant and O'Neal also recognise that there are additional problems with autocorrelation when percentages are used.
[2] Warther (1995), in a study on aggregate flows, normalizes the fund flows by dividing them by total stock market value at the end of the previous month. He recognizes that, since the denominator is a function of lagged returns, there is a risk of spurious correlations in the regressions. Use of total net fund assets as the normalizing variable results in non-stationary variances.

correct for any scale effects induced by the total dollar fund flow measure. Similarly the older, more established, funds have a greater potential to attract money flow than do newer funds, and therefore the age of the fund is included. Expenses are also incorporated since a fund with a higher expense ratio, other things being equal, is not as attractive to investors as those with lower fees. The relevance of size, age and expenses has been established by Del Guercia and Tkac (2002), Santini and Aber (1998), Sirri and Tufano (1998).

Huang, Wei and Yan (2004) also considered the impact of fund volatility on money flows. We take a broader approach to volatility and consider it from a market perspective. Indeed investors will consider the performance/risk relation of the fund in their selection process however, this selection may be tempered by market events. Further the decision to select a fund may be influenced by the events in the bond market and a general perception of investment activity. We therefore incorporate the return on the bond market and the VIX index,[3] as a measure of volatility, controlling for the changes in flows due to investor sentiment.

The main aim of our analysis is to examine the contemporaneous flow-performance relation of mutual funds at the individual fund level, and develop a model that recognises a joint causal linkage between fund flows and fund returns. Thus, in line with the foregoing discussion, we begin with a two-equation base case model specification in which (a) equation 1 models fund returns as a function of contemporaneous fund flows; lagged flows; lagged own-fund returns; contemporaneous and lagged aggregate market returns; and (b) equation 2 models fund flows as a function of contemporaneous and lagged own-fund returns; lagged flows; contemporaneous and lagged bond market returns; fund size; the VIX index; fund age and fund expenses; as follows:

[3] Whaley (2000) has helped popularize the notion that the VIX can be viewed as an "investor fear gauge". As such, the index tends to reach very high levels at times when investors are feeling particularly anxious about equity markets.

Model 1 – The Base Case Model

$$r_{it} = \beta_0 + \beta_1 fl_{it} + \beta_2 fl_{i,t-1} + \beta_3 r_{i,t-1} + \beta_4 m_t + \beta_5 m_{t-1} + \varepsilon_{it} \quad (1)$$

$$fl_{it} = \lambda_0 + \lambda_1 r_{it} + \lambda_2 fl_{i,t-1} + \lambda_3 r_{i,t-1} + \lambda_4 bm_t + \lambda_5 bm_{t-1} + \lambda_6 s_{i,t-1} + \lambda_7 v_{t-1} + \lambda_8 a_{i,t} + \lambda_9 e_{i,t} + \mu_{it} \quad (2)$$

$$\text{instrumental variables} = fl_{i,t-1}, r_{i,t-1}, m_t, m_{t-1}, bm_t, bm_{t-1}, s_{i,t-1}, v_{t-1}, a_{i,t}, e_{i,t}$$

where: r_{it} = return on fund i at time t

fl_{it} = net fund flow to fund i at time t, calculated as: $TNA_t - TNA_{t-1}(1+r_t)$ and TNA = total net assets.

m_t = return on the market at time t, proxied by S&P 500,

bm_t = return on the bond market at time t,

s_{it} = size of fund i at time t measured as log of the total net assets.

v_t = VIX volatility index from CBOE (represents annualized implied daily aggregate market volatility. The end of month observation is divided by the square root of 12 to translate to monthly volatility)

$a_{i,t}$ = age in months of fund i at time t

$e_{i,t}$ = annual expense ratio of fund i at time t

To determine the most appropriate method for analysis we run a Hausman's test for endogeneity (Hausman, 1978). Hausman's test compares the estimated coefficient(s) of the relevant (*k*) variable(s) produced using OLS with the counterpart value produced using an instrumental variables estimation approach, that is:

$$H = (\hat{\beta}_{OLS} - \hat{\beta}_{IV})'[V\hat{a}r(\beta_{IV}) - V\hat{a}r(\beta_{OLS})]^{-1}(\hat{\beta}_{OLS} - \hat{\beta}_{IV})$$

Under the null hypothesis $\hat{\beta}_{OLS}$ is consistent and efficient, while $\hat{\beta}_{IV}$ is efficient. We reject the null hypothesis that OLS is efficient and consistent, at the 1% level, for both equations. Accordingly, we estimate model 1 using pooled two stage least squares regression (2SLS).

We run a series of robustness tests. First, we estimate the base case model applying an instrumental variables approach using Generalised Method of Moments (GMM IV). GMM IV is more robust as it allows for heteroskedasticity and autocorrelation consistent (HAC) standard errors, non normal disturbances and correlations across equations. Second, we also extend our model to incorporate a series of variables that may impact on how flow and performance interact at the contemporaneous level. The intention is to establish that our initial results are fully robust to established linkages as identified in the literature. Five independent issues are addressed: (a) business cycle effects; (b) asymmetry of fund returns; c) retail versus institutional fund classifications, (d) new funds and (e) multiple lags.

3.2 Model Extensions – Planned Robustness Checks

3.2.1 Business Cycle Effects

Fund returns and flows will be influenced by general economic activity. Lynch, Wachter and Boudry (2003) question if mutual fund performance varies over the business cycle. They use dividend yield as the information variable to assess conditional performance and find fund performance does move with the business cycle. In our study some of the macro-phenomena will be captured by the bond and share market returns and investor sentiment (VIX) within Model (1), but the linkages are unlikely to be stable over the entire period of the study. Accordingly, we create a dummy variable related to business cycles to more broadly take into account the potential moderating effect of economic conditions. Convention suggests a dichotomous classification: the business cycle is identified as either being in a period of expansion or a period of contraction.[4] The business cycle phases are captured by a dummy variable (*cyc*) which is incorporated into the base case model to produce Model 2 as follows:

[4] Relevant to the timeframe of our study NBER identify the following cycle phases: January 1991 to March 1991 as a contraction phase; April 1991 to March 2001 an expansionary phase and April 2001 to November 2001 as a contraction. Although no peak has been identified since this time we take December 2001 to December 2004 to be a non-contraction period.

Model 2 – Business Cycle Enhanced Model

$$r_{it} = \beta_0 + \beta_1 fl_{it} + \beta_2 fl_{i,t-1} + \beta_3 r_{i,t-1} + \beta_4 m_t + \beta_5 m_{t-1} + \beta_6 cyc + \beta_7 cyc.fl_{it} + \beta_8 cyc.fl_{i,t-j} + \varepsilon_{it} \quad (3)$$

$$fl_{it} = \lambda_0 + \lambda_1 r_{it} + \lambda_2 r_{i,t-1} + \lambda_3 fl_{i,t-1} + \lambda_4 bm_t + \lambda_5 bm_{t-j} + \lambda_6 s_{i,t-1} + \lambda_7 v_{t-1} + \lambda_8 a_{i,t} + \lambda_9 e_{i,t} + \lambda_{10} cyc + \lambda_{11} cyc.r_{it} + \lambda_{12} cyc.r_{i,t-j} + \mu_{it} \quad (4)$$

$$\text{instrumental variables} = fl_{i,t-1}, r_{i,t-1}, m_t, bm_t, m_{t-1}, bm_{t-1}, s_{i,t-1}, v_{t-1}, a_{i,t}, e_{i,t}, cyc, cyc.fl_{i,t-1}, cyc.r_{i,t-1}$$

where cyc = 1 for a non-contraction period, 0 otherwise.

3.2.2 Convexity in the Flow-return Relation

The literature is extensive with respect to the convexity between performance and flow reactions; (see, for example, Ippolitto, 1992; Siri and Tufano, 1998). A good performing fund attracts a higher level of fund flows; whereas, poor performing funds do not lose money flows at the same rate. To explore this asymmetry, we rank funds each month on the basis of return. The extreme performers are isolated, in line with previous research, to ensure a clear testing of the performance asymmetry hypothesis. Specifically, in each month funds that are in the top 5% or the bottom 5% in raw return performance are identified and two dummy variables are created to represent each of these categories. Accordingly, in Model 3 the base case model is extended to consider asymmetry in fund returns by incorporating the two dummy variables as follows:[5]

Model 3 – Asymmetry in Returns Enhanced Model

$$r_{it} = \beta_0 + \beta_1 fl_{it} + \beta_2 fl_{i,t-1} + \beta_3 r_{i,t-1} + \beta_4 m_t + \beta_5 m_{t-1} + \varepsilon_{it} \quad (5)$$

$$fl_{it} = \lambda_0 + \lambda_1 Dbt_{t-1} + \lambda_2 Dtp_{t-1} + \lambda_3 r_{it} + \lambda_4 fl_{i,t-1} + \lambda_5 r_{i,t-1} + \lambda_6 Dbt_{t-1} r_{i,t-1} + \lambda_7 Dtp_{t-1} r_{i,t-1} + \lambda_8 bm_t + \lambda_9 bm_{t-1} + \lambda_{10} s_{i,t-1} + \lambda_{11} v_{t-1} + \lambda_{12} a_{i,t} + \lambda_{13} e_{i,t} + \mu_{it} \quad (6)$$

$$\text{instrumental variables: } fl_{i,t-1}, r_{i,t-1}, m_t, m_{t-1}, bm_t, bm_{t-1}, s_{i,t-1}, v_{t-1}, a_{i,t}, e_{i,t}, Dbt_{t-1}, Dbt_{t-1} r_{i,t-1}, Dtp_{t-1}, Dtp_{t-1} r_{i,t-1}$$

where: Dtp_{it} = 1 if $r_{i,t}$ belongs to the top 5% of all funds at time t, 0 otherwise.

[5] For completeness we also considered a possible asymmetry in fund flows. Our analysis showed that there was not significant asymmetric relation in this setting and so we suppress details to conserve space.

Dbt_{it} = 1 if $r_{i,t}$ belongs to the bottom 5% of all funds at time t, 0 otherwise.

3.2.3 Retail versus Institutional Funds

The money flows experienced by retail and institutional funds are likely to vary as a result of the different markets these sectors serve. James and Karceski (2003) find that while there is a difference in the performance of retail and institutional funds; institutional fund flows are less sensitive to performance than retail fund flows. Further, they distinguish 'institutional funds with retail mates' and argue that these funds may attract a less sophisticated clientele. They find that the lack of a flow/performance linkage in the institutional funds can be explained by the more sophisticated performance measures that this group of investors implement. Accordingly, we classify each fund into one of three categories: (a) retail, (b) institutional or (c) both retail and institutional and we incorporate three associated dummy variables into the base case model to distinguish between them. Model 4 shows the adjusted base case model with dummies included to separate the relation for retail versus wholesale funds.

Model 4 – Fund Classification Enhanced Model

$$\begin{aligned} r_{it} &= \beta_0 + \beta_1 fl_{it} + \beta_2 fl_{i,t-1} + \beta_3 r_{i,t-1} + \beta_4 m_t + \beta_5 m_{t-1} + \beta_6 Dio_{t-1} + \beta_7 Dio_{t-1} fl_{it-1} + \\ &\quad \beta_8 Dib_{t-1} + \beta_9 Dib_{t-1} fl_{it-1} + \varepsilon_{it} \end{aligned} \tag{7}$$

$$\begin{aligned} fl_{it} &= \lambda_0 + \lambda_1 r_{it} + \lambda_2 fl_{i,t-j} + \lambda_3 r_{i,t-j} + \lambda_4 Dio_{t-1} + \lambda_5 Dio_{t-1} r_{i,t-1} + \lambda_6 Dib_{t-1} + \lambda_7 Dib_{t-1} r_{i,t-1} \\ &\quad + \lambda_8 bm_t + \lambda_9 bm_{t-j} + \lambda_{10} s_{i,t-j} + \lambda_{11} v_{t-j} + \lambda_{12} a_{i,t} + \lambda_{13} e_{i,t} + \mu_{it} \end{aligned} \tag{8}$$

instrumental variables: $fl_{i,t-j}, r_{i,t-j}, m_t, m_{t-1}, bm_t, bm_{t-1}, s_{i,t-j}, v_{t-j}, a_{i,t}, e_{i,t}, Dio_{t-1},$
$Dio_{t-1} fl_{it-1}, Dio_{t-1} r_{i,t-1}, Dib_{t-1}, Dib_{t-1} fl_{it-1}, Dib_{t-1} r_{i,t-1}$

where: $Dio_t = 1$ if the fund is classified as an institutional fund only, 0 otherwise

$Dib_t = 1$ if the fund is classified as both an instituional and retail fund, 0 otherwise.

3.2.4 ' New' versus 'less New' Funds

We also consider the possibility that 'new' funds exhibit a relation different from other 'less new' (and, thus, more established) funds. Chevalier & Ellison (1997) find that the flow/performance relation provides different incentives for managers of younger funds as compared to older funds. A new fund in its early development is likely to experience different patterns of flows than an established fund. Flows for younger funds are expected to be relatively large and the lack of historical information means that investors are unable to rely on past performance. Investors may also be more forgiving with their investment choices on the basis of early performance results, that is, we would not expect an investor in a new fund to withdraw in the first few months if performance does not immediately meet expectations. Further, the performance of a new fund is less likely to be affected by cash inflows since the expectation of the manager is to engage in major portfolio construction based on anticipated large initial flows. Hence, the placement is likely to be well planned. Withdrawals of funds are expected to be lower than for other funds – hence, the anticipated performance effect here is limited. Model 5 adapts the base case model by incorporating an appropriately defined dummy variable for new funds, as follows:

Model 5 – 'New' Fund Enhanced Model

$$r_{it} = \beta_0 + \beta_1 fl_{it} + \beta_2 fl_{i,t-j} + \beta_3 r_{i,t-j} + \beta_4 m_t + \beta_5 m_{t-j} + \beta_6 Dnf_{t-1} + \beta_7 Dnf_{t-1} fl_{it} + \varepsilon_{it} \qquad (9)$$

$$\begin{aligned} fl_{it} = {} & \lambda_0 + \lambda_1 r_{it} + \lambda_2 fl_{i,t-j} + \lambda_3 r_{i,t-j} + \lambda_4 bm_t + \lambda_5 bm_{t-j} + \lambda_6 s_{i,t-j} + \lambda_7 v_{t-j} + \lambda_8 a_{i,t} + \\ & \lambda_9 e_{i,t} + \lambda_{10} Dnf_{t-1} + \lambda_{12} Dnf_{t-1} r_{i,t-j} + \mu_{it} \end{aligned} \qquad (10)$$

instrumental variables: $fl_{i,t-j}, r_{i,t-j}, m_t, m_{t-1}, bm_t, bm_{t-1}, s_{i,t-j}, v_{t-j}, a_{i,t}, e_{i,t},$
$Dnf_{t-1}, Dnf_{t-1} fl_{i,t-j}, Dnf_{t-1} r_{i,t-j}$

where: $Dnf_t = 1$ if age ≤ 12 months, 0 otherwise.

3.2.5 Multiple Lags

As a final robustness check we extend the base case model to incorporate 6 lags on the key variables to control for any spurious relation between past returns and flows as follows in Model 6:

Model 6 – Multiple Lags Enhanced Model

$$r_{it} = \beta_0 + \beta_1 fl_{it} + \sum_{j=1}^{6} \beta_{1+j} fl_{i,t-j} + \sum_{j=1}^{6} \beta_{7+j} r_{i,t-j} + \sum_{j=0}^{6} \beta_{14+j} m_{t-j} + \varepsilon_{it} \tag{11}$$

$$\begin{aligned} fl_{it} = {} & \lambda_0 + \lambda_1 r_{it} + \sum_{i=1}^{6} \lambda_{1+j} r_{i,t-j} + \sum_{j=1}^{6} \lambda_{7+j} fl_{i,t-j} + \sum_{j=0}^{6} \lambda_{14+j} bm_{t-j} + \sum_{i=1}^{6} \lambda_{20+j} s_{i,t-j} \\ & + \lambda_{27} v_{t-1} + \lambda_{28} a_{i,t} + \lambda_{29} e_{i,t} + \mu_{it} \end{aligned} \tag{12}$$

instrumental variables = $fl_{i,t-j}, r_{i,t-j}, m_t, m_{t-j}, bm_t, bm_{t-j}, s_{i,t-j}, v_{t-1}, a_{i,t}, e_{i,t}$; where j = 1 to 6.

3.3 Data and Sampling

We examine all the domestic equity funds listed on the CRSP mutual fund database. The database is free of survivorship bias. We extract monthly fund return, total net assets, age and expense data for each fund. Monthly total asset data are only available from 1991 therefore our study examines the period January 1991 to December 2004. From the list of domestic equities we omit index funds and our final sample comprises 7390 funds. Of these funds 393 have a full 14 years of return data. The average sample life, across all funds with return data, is 6.06 years. There are 3863 funds with at least 5 years of data and 1265 funds with less than 2 years of data. The average age of the funds that existed as at 31 December 2004 is 7.67 years. The sample comprises 1227 institutional funds, 2617 retail and 3194 'mixed' funds i.e. those that are classified as both institutional and retail. There are 352 with neither classification.

We use the S&P 500 as the market index benchmark and the 20-year bond return in our analysis. Data for both of these variables are accessed from CRSP. For model extensions we utilize the VIX index of (annualized) implied volatility for the S&P500,[6,7] obtained from the

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[6] Generally, it has found that VIX provides high quality forecasts of future realised volatility – see, for example, Corrado and Miller (2004).

[7] The VIX was originally calculated based on prices of the S&P100 index options using near the money strikes. In September 2003, the benchmark index was changed to the S&P500 index and the formula used to calculate the VIX modified to take into account a broader range of strike prices which are weighted with near the money strikes having the greatest weight. The CBOE calculated a historical series of the new S&P500 based VIX and continues to provide the S&P100 based VIX, but under the new ticker symbol VXO. Full details of the algorithm used to calculate these implied volatilities is described in a white paper at the CBOE's website: http://www.cboe.com/micro/vix/vixwhite.pdf.

website of the Chicago Board Options Exchange (CBOE) and US business cycle information obtained from the website of the National Bureau of Economic Research (NBER)[8].

Table 1 shows some basic descriptive statistics for the sample data. In Panel A, it is interesting to note the large range in fund returns, flows and total net assets. In Panel B, correlations are reported and we see a high positive correlation (0.72) between fund return and market return and a negative correlation (-0.18) between funds return and bond return. Given our sample comprises equity funds these correlations are not surprising.

4. Results

4.1 Base Case Model Estimation (Model 1)

The results for Model 1 are presented in Table 2. The table is divided into two panels – the left hand side (Panel A) reports the 2SLS outcome, while Panel B reports the GMM IV results. Focusing on Panel A, several key features are worthy of note. First, there is a significant negative coefficient on the flow variable in the return equation (equation 1). This result shows that as concurrent flow increases, returns decrease, consistent with our predictions that fund managers are required to make decisions that may be sub-optimal as a result of the need for rapid placement of new money[9]. With regard to negative contemporaneous flows it is also consistent with managers being able to quickly utilize available cash balances to meet withdrawals, which in the short term will lead to a higher average performance of funds under management (since the temporary weighting of low yielding cash assets will decline during these periods of investor withdrawal).

Second, it is notable that the preceding interpretation is only relevant for the current flows, since the lagged flow variable has a significant positive coefficient in the return equation. With regard to cash inflows this shows that managers are able to react to flows from the previous

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[8] http://www.nber.org/cycles/

[9] In is interesting to note that when model 1 is estimated using OLS, that is ignoring endogeneity, we find flow has significant positive effect on return.

months in an effective manner. Specifically, prior period inflows have a positive impact on returns, suggesting that managers overcome the initial 'setback' of not being able to immediately place new money in the desired assets. Interestingly, these results also suggest that with regard to the cash outflows, the initial "positive" impact on performance is reversed in later periods – in part, this may reflect the re-instatement of the cash liquidity buffer which will have the effect of inducing a lower average return across fund asset holdings.

Third, in the fund flow equation (equation 2) of Model 1 there are significant positive coefficients on the fund return and lagged fund return variables. Flow is a function of past return and more importantly a function of concurrent return. As returns increase, flows are also increasing. This result is a significant finding for this literature, since it demonstrates that investors assess the performance of fund in timely manner and react to this information in the expected direction. The majority of prior work that examines factors determining flows, focus on past performance following Sirri and Tufano (1998). We note that Deaves (2004) employed contemporaneous performance (using annual measures) in an analysis of Canadian fund flows, but the fact that it involved annual sampling renders the 'contemporaneous' label somewhat misleading.

Our key finding in the base case model is clear: allowing for the endogenous nature of the two central variables, we document strong contemporaneous relations between returns and flows. Notably, we find that this linkage is bi-directional and that it is 'asymmetric' in the sense that the linkage is positive in one direction, while negative in the other.

Our control variables in each equation are also, in general, significant. First, we see that fund returns are a function of past fund return and market return. As expected the current market return coefficient is highly significant and close to unity. Second, money flow into funds is also a function of past bond return but not current bond return. However, the estimated lagged coefficient, being positive, is not in the expected direction. Other things equal, we would expect that if bond returns are increasing, flows to equity mutual funds would decrease. This result is unexpected given that there is a (univariate) negative correlation between fund return and bond return. The negative coefficient in the multivariate setting suggests lagged bond return has a more complex role, than is apparent based on univariate considerations.

Third, last period's fund size has a significant and positive impact on flows . The positive coefficient on the size variable suggests larger flows go to larger funds, as expected. Fourth, the estimated coefficient on the lagged VIX index is negative and significant. This suggests that as the VIX index increases, investors perceive higher volatility which suggests a negative market sentiment. As such, the VIX results indicate that investors invest less in equities, the higher is the value of the VIX. In other words, the negative VIX coefficient shows that flows to equity funds are decreasing as the 'fear index' increases. This is intuitively appealing.

Fifth, the coefficient on age is negative showing that the older funds have smaller flows. This result is a little perplexing – this issue is further explored in a subsequent variation of the base case model.[10] The expense coefficient is also negative showing that the more expensive funds attract fewer flows.

Turning now to the GMM IV results presented in Panel B. Our key results are maintained in this estimation. Current flow has a negative impact on fund return and current return has a positive impact on fund flow. We note that in Panel B the control variables in Equation 2 are not significant. The lower power in our t statistics is expected as GMM accounts for the cross sectional correlations. We interpret these t statistics as a 'reality' check on the apparent significance in the 2SLS case. The important conclusion from the GMM IV results is that there are strong contemporaneous relations between returns and flows. Our key results are robust to this alternative estimation procedure.

[10] New funds indeed would attract more flows as they experience high early growth but we would also expect the established funds to be attracting flows. By separating new funds we expect the impact of the age variable to decrease.

4.2 Extension to the Base Case Model – Outcome of Robustness Checks

4.2.1 Business Cycle Enhanced Model (Model 2)

The 2SLS results for estimating Model 2, are presented in Table 3.[11] Model 2 incorporates a (dummy) variable to reflect the business cycle. First, and most importantly, the contemporaneous relationship between flows and returns is maintained in this model. As before, contemporaneous flow has a negative role in the returns equation, while contemporaneous return has a positive impact on flows. Second, focusing on the business cycle variables, the results show that the cycle is relevant in the determination of returns (Panel A) but does not affect the relationship of flows on returns. However, in the determination of fund flows (Panel B), business cycle is found to be very relevant. An expansion cycle has a positive effect on flow but the coefficient on return (λ_1) is positive for contractions yet negative for expansions ($\lambda_1 + \lambda_{11}$). This is a puzzling result. We previously identify a positive relation between current returns and flows. Now we find in an expansionary period, when returns are presumably increasing, the impact on flows is negative.

Note however, that the bond return (Panel B) is now in the expected direction. During expansionary periods investors are perhaps investing in multiple opportunities. The lagged return impact on flows in a contraction cycle is positive (λ_2); while the incremental effect in expansions is significantly negative (λ_{12}) – sufficiently so, to produce no impact of lagged return on flows in this part of the business cycle. This result shows investors are perhaps less discerning in a growth stage and less focused on chasing returns. Third, the VIX index in this model changes to a positive coefficient (λ_7). It seems that, by introducing a cycle variable into the model the market sentiment variable carries less weight and the increase in volatility is not inducing caution towards investment flows. Rather, flow increases with volatility and, thus, we believe that the cycle variable is capturing much of the investor sentiment in this model setting.

[11] For the remainder of the analysis we report 2SLS results only, in order to conserve space.

4.2.2 Asymmetry in Returns Enhanced Model (Model 3)

Model 3 incorporates a dummy variable to recognize the asymmetry in the flow/performance relationship for good and poor performers (equation 6). The results are presented in Table 4. Again, our primary concern is what impact the changed model has on our key finding on contemporaneous linkages between returns and flows (negative) and between flows and returns (positive). Once more, we establish a strongly robust result in this regard – accommodating asymmetric returns does not matter.

With regard to the secondary findings, a few comments are worthwhile. Prior literature suggests past positive returns will result in higher flows. Our results are consistent with this view. The coefficients on the dummy variables for the top and bottom performing funds are positive and negative, respectively. Turning to the interaction of the dummies with the lagged returns variable, the relationship between lagged return and flows for the top performing funds is positive ($\lambda_5+\lambda_7$), although notably lower than the majority of funds in the 5^{th} – 95^{th} percentile range. For the bottom performers the coefficient on lagged return is negative (λ_6), emphasizing that funds which perform poorly, experience more negative flows in the subsequent period. However, we must bear in mind that this coefficient is an increment relative to the (5-95%) base case (λ_5) – it is seen that these coefficients are of very similar magnitude, thus effectively canceling each other out. That is, lagged returns have very little impact on flows for the most extreme losing funds in our sample.

4.2.3 Fund Classification Enhanced Model (Model 4)

Table 5 presents the results for Model 4. Notably, the introduction of the retail and institutional classifications does not change our conclusions with respect to our contemporaneous variables. For retail funds, lagged flow has a positive effect on return (Panel A, β_2). However, for institutional funds the effect is negative ($\beta_2+\beta_7$), demonstrating the difficulty of placing institutional money. In the flow equation (Panel B), past return has a greater positive effect on flow for the retail funds (λ_3). The effect of institutionals is still positive but significantly lower (λ_3+λ_5) . This result is consistent with James and Karceski (2003) who find flows into institutional funds are less sensitive to performance than the flows into retail funds.

4.2.4 'New' Fund Enhanced Model (Model 5)

Model 5 incorporates the potential impact of 'new' funds and the results are presented in Table 6. Again, there is no change to our conclusions with respect to the key variables. However, it is noteworthy that the returns on new funds are less sensitive to past flows (Panel A). New funds are generating relatively high inflows and the speed of placement in line with the asset allocation decision is perhaps more difficult. Flows remain sensitive to past return and past flow but not to the same extent as more established funds (Panel B). This result demonstrates the new money coming in, irrespective of prior activity. Investors are likely to be responding to other sources of information for these funds.

4.2.5 Multiple Lags Enhanced Model (Model 6)

Finally, Model 6 is estimated as a robustness check to consider the relevance of multiple past lags and the results are presented in Table 7. The findings on our key variables remain consistent with Model 1. In Panel A the lagged flow variables are significant and positive for all 6 lags although the magnitude of the coefficients is greater for the first 3 lags. Managers are able to use past flows to enhance returns although older flows have the least impact. Flows from 2 months prior have a greater positive effect than one month prior flows consistent with managers needing some time to effectively place the new inflows or temper the impact of outflows. In Panel B lagged return is significant for lags 1 to 5. The one month prior return has the highest coefficient and, hence, the most impact on flows. Subsequent lags are of decreasing importance. We note in this model that the coefficient on the current return variable is not as large as the coefficient on the one-lag return, confirming the results of previous studies that last period's performance is very relevant in determining fund flow. Nevertheless, the impact of current return is significant and positive, as consistently demonstrated throughout all our models.

5. Conclusions

In this study we test for and find an endogenous relation between mutual fund flow and returns. Accordingly, we account for the endogeneity in our estimation model and find a contemporaneous relation between mutual fund flows and returns. Current flows have a negative impact on returns consistent with fund managers finding it difficult to quickly place large inflows of cash. Lagged flows have a positive effect on return showing that these inflows are effectively invested and enhance the fund return. In turn these current positive returns together with past returns have a positive impact on flow. Investors are quick to recognize the high performing funds and money follows.

Our key results are robust to different estimation methods – 2SLS and GMM IV. We also perform a battery of robustness checks of our results to the inclusion of various other factors, identified in the literature, which may impact on fund returns and flows. Of greatest importance, the contemporaneous relation between flows and returns is maintained for each of these tests. We confirm a number of linkages that have been demonstrated in the prior literature. Specifically, we show that there is an asymmetric relation between past returns and flows. Further, we find that the business cycle is relevant in the determination of factors that affect flows. Finally, we see that institutional fund flows are less sensitive to lagged returns and the returns on new funds are less sensitive to past flows.

Understanding the flow performance relation has been the subject of extensive academic research and is of practical importance to managers in attracting new investment. Our paper demonstrates that the joint assessment of flows and performance must consider the endogenous relationship. From a managers perspective the need to grow the fund through flows also has a return impact. Similarly, the return of the fund is a key driver in determining investor flows. Ultimately both issues simultaneously influence the overall fund evaluation.

Table 1: Descriptive Statistics and Correlations

Panel A: Basic Descriptive Statistics

	Fund Flow (millions)	Fund Return (monthly percentage)	Total Net Assets (millions)	Bond Return (monthly percentage)	S&P 500 (monthly percentage)	Treasury Notes (monthly percentage)
Mean	1.98	0.0080	454.92	0.0066	0.0107	0.0032
Median	0.04	0.0112	42.23	0.0078	0.0135	0.0037
Maximum	6336.89	2.3541	109796.20	0.0549	0.1141	0.0060
Minimum	-7094.87	-0.7711	0.00	-0.0668	-0.1437	0.0006
Std. Dev.	42.33	0.0598	2301.11	0.0199	0.0414	0.0014
# Observations	536,628	564,006	545,240	168	168	168

Panel B: Correlations

	Fund Flow	Fund Return	Total Net Assets	Bond Return	S&P 500	Treasury Notes
Fund Flow	1.00					
Fund Return	0.04	1.00				
Total Net Assets	0.07	0.00	1.00			
Bond Return	-0.01	-0.18	0.00	1.00		
S&P 500	0.02	0.72	0.01	0.00	1.00	
Treasury Notes	0.02	0.00	0.04	0.12	0.09	1.00

Table 2: Estimation Results for Base Case Model (Model 1)

This table reports the outcome of estimating the following two-equation model:

$$r_{it} = \beta_0 + \beta_1 fl_{it} + \beta_2 fl_{i,t-1} + \beta_3 r_{i,t-1} + \beta_4 m_t + \beta_5 m_{t-1} + \varepsilon_{it} \quad (1)$$

$$fl_{it} = \lambda_0 + \lambda_1 r_{it} + \lambda_2 fl_{i,t-1} + \lambda_3 r_{i,t-1} + \lambda_4 bm_t + \lambda_5 bm_{t-1} + \lambda_6 s_{i,t-1} + \lambda_7 v_{t-1} + \lambda_8 a_{i,t} + \lambda_9 e_{i,t} + \mu_{it} \quad (2)$$

$$\text{instrumental variables} = fl_{i,t-1}, r_{i,t-1}, m_t, m_{t-1}, bm_t, bm_{t-1}, s_{i,t-1}, v_{t-1}, a_{i,t}, e_{i,t}$$

where r_{it} = return on fund i at time t; fl_{it} = net fund flow to fund i at time t; m_t = return on the market at time t, proxied by S&P 500; bm_t = return on the bond market at time t; s_{it} = size of fund i at time t measured as log of the net total assets; v_t = volatility index from CBOE (the VIX index represents implied annualized daily volatility. The end of month observation is divided by the square root of 12 to translate to monthly volatility); $a_{i,t}$ = the age in months of fund i at time t; $e_{i,t}$ = the annual expense ratio of fund i. Estimation is performed using 2SLS (Panel A) and GMM IV (Panel B).

	Panel A: Two Stage Least Squares			Panel B: GMM IV		
		Coefficient	t-statistic		Coefficient	t-statistic
Equation 1 - Dependent Variable: Fund Return						
Constant β_0	β_0	0.0018	19.23	β_0	0.0007	1.77
Flow (fl_{it})	β_1	-0.0009	-15.55	β_1	-0.0009	-2.25
Lagged Flow ($fl_{i,t-1}$)	β_2	0.0004	15.52	β_2	0.0007	2.19
Lagged Return ($r_{i.t-1}$)	β_3	0.0210	8.05	β_3	0.1129	3.86
Market Return (m_t)	β_4	0.9784	458.87	β_4	0.8534	40.13
Lagged Market Return (m_{t-1})	β_5	0.0592	20.91	β_5	0.0084	0.33
Adjusted R^2			0.1642			
Equation 2 - Dependent Variable: Fund Flow						
Constant λ_0	λ_0	0.8519	3.50	λ_0	3.3984	2.32
Return (r_{it})	λ_1	20.5293	15.34	λ_1	37.3301	2.912
Lagged Flow ($fl_{i,t-1}$)	λ_2	0.3858	286.29	λ_2	0.7437	21.11
Lagged Return ($r_{i.t-1}$)	λ_3	19.2747	20.48	λ_3	19.1549	2.53
Bond Return (bm_t)	λ_4	0.6911	0.26	λ_4	-2.0309	-0.14
Lagged Bond Return (bm_{t-1})	λ_5	8.5872	3.36	λ_5	12.3002	0.80
Lagged Size (s_{t-1})	λ_6	0.5528	22.77	λ_6	-0.1147	-0.41
Lagged VIX (v_{t-1})	λ_7	-0.2045	-6.35	λ_7	-0.5414	-3.09
Age (a_t)	λ_8	-0.0071	-15.68	λ_8	0.0015	0.67
Expenses (e_t)	λ_9	-0.0169	-3.99	λ_9	-4.4558	-0.75
Adjusted R^2			0.158			

Table 3: Estimation Results for Business Cycle Enhanced Model (Model 2)

This table reports the outcome of estimating the following two-equation model:

$$r_{it} = \beta_0 + \beta_1 fl_{it} + \beta_2 fl_{i,t-1} + \beta_3 r_{i,t-1} + \beta_4 m_t + \beta_5 m_{t-1} + \beta_6 cyc + \beta_7 cyc.fl_{it} + \beta_8 cyc.fl_{i,t-j} + \varepsilon_{it} \quad (3)$$

$$fl_{it} = \lambda_0 + \lambda_1 r_{it} + \lambda_2 r_{i,t-1} + \lambda_3 fl_{i,t-1} + \lambda_4 bm_t + \lambda_5 bm_{t-j} + \lambda_6 s_{i,t-1} + \lambda_7 v_{t-1} + \lambda_8 a_{i,t} + \lambda_9 e_{i,t} + \lambda_{10} cyc + \lambda_{11} cyc.r_{it} + \lambda_{12} cyc.r_{i,t-j} + \mu_{it} \quad (4)$$

$$\text{instrumental variables} = fl_{i,t-1}, r_{i,t-1}, m_t, bm_t, m_{t-1}, bm_{t-1}, s_{i,t-1}, v_{t-1}, a_{i,t}, e_{i,t}, cyc, cyc.fl_{i,t-1}, cyc.r_{i,t-1}$$

where r_{it} = return on fund i at time t; fl_{it} = net fund flow to fund i at time t; m_t = return on the market at time t, proxied by S&P 500; cyc =1 for a peak cycle, 0 otherwise; bm_t = return on the bond market at time t; s_{it} = size of fund i at time t measured as log of the net total assets; v_t = volatility index from CBOE (the VIX index represents implied annualized daily volatility. The end of month observation is divided by the square root of 12 to translate to monthly volatility); $a_{i,t}$ = the age in months of fund i at time t; $e_{i,t}$ = the annual expense ratio of fund i. Estimation is performed using 2SLS.

Panel A: Equation 3 - Dependent Variable Fund Return				Panel B: Equation 4 - Dependent Variable Fund Flow			
		Coefficient	t-statistic			Coefficient	t-statistic
Constant β_0	β_0	0.0013	14.84	Constant λ_0	λ_0	-4.0054	-4.73
Flow (fl_{it})	β_1	-0.0004	-9.00	Return (r_{it})	λ_1	95.0534	7.61
Lagged Flow ($fl_{i,t-1}$)	β_2	0.0002	9.01	Lagged Return ($r_{i.t-1}$)	λ_2	15.4984	10.38
Lagged Return ($r_{i.t-1}$)	β_3	0.0072	3.25	Lagged Flow ($fl_{i,t-1}$)	λ_3	0.3861	275.76
Market Return (m_t)	β_4	0.9723	391.11	Bond Return (bm_t)	λ_4	-52.6057	-5.82
Lagged Market Return (m_{t-1})	β_5	0.0707	29.36	Lagged Bond Ret (bm_{t-1})	λ_5	12.9515	4.68
Business Cycle (cyc)	β_6	0.0018	5.50	Lagged Size (s_{t-1})	λ_6	0.5846	22.67
Business Cycle x flow ($cyc.fl_{it}$)	β_7	-0.0008	-1.82	Lagged VIX (v_{t-1})	λ_7	0.4841	4.07
Business Cycle x lagged Flow ($cyc.fl_{i,t-1}$)	β_8	0.0001	1.00	Age (a_t)	λ_8	-0.0069	-14.60
				Expenses (e_t)	λ_9	-0.0205	-4.61
				Business Cycle (cyc)	λ_{10}	1.1068	3.18
				Business Cycle x Return (cyc,r_{it})	λ_{11}	-512.20	-6.01
				Business Cycle x lagged Return ($cyc.r_{i,t-1}$)	λ_{12}	-13.6662	-4.55
Adjusted R^2			0.4023	Adjusted R^2			0.0923

Table 4: Estimation Results for Asymmetry in Returns Enhanced Model (Model 3)

This table reports the outcome of estimating the following two-equation model:

$$r_{it} = \beta_0 + \beta_1 fl_{it} + \beta_2 fl_{i,t-1} + \beta_3 r_{i,t-1} + \beta_4 m_t + \beta_5 m_{t-1} + \varepsilon_{it} \quad (5)$$

$$fl_{it} = \lambda_0 + \lambda_1 Dbt_{t-1} + \lambda_2 Dtp_{t-1} + \lambda_3 r_{it} + \lambda_4 fl_{i,t-1} + \lambda_5 r_{i,t-1} + \lambda_6 Dbt_{t-1} r_{i,t-1} + \lambda_7 Dtp_{t-1} r_{i,t-1}$$
$$+ \lambda_8 bm_t + \lambda_9 bm_{t-1} + \lambda_{10} s_{i,t-1} + \lambda_{11} v_{t-1} + \lambda_{12} a_{i,t} + \lambda_{13} e_{i,t} + \mu_{it} \quad (6)$$

instrumental variables: $fl_{i,t-1}, r_{i,t-1}, m_t, m_{t-1}, bm_t, bm_{t-1}, s_{i,t-1}, v_{t-1}, a_{i,t}, e_{i,t},$

$$Dbt_{t-1}, Dbt_{t-1} r_{i,t-1}, Dtp_{t-1}, Dtp_{t-1} r_{i,t-1}$$

where r_{it} = return on fund i at time t; fl_{it} = net fund flow to fund i at time t; m_t = return on the market at time t, proxied by S&P 500; Dtp_{it} = 1 if $r_{i,t}$ belongs to the top 5% of all funds, 0 otherwise; Dbt_{it} = 1 if $r_{i,t}$ belongs to the bottom 5% of all funds, 0 otherwise; bm_t = return on the bond market at time t; s_{it} = size of fund i at time t measured as log of the net total assets; v_t = volatility index from CBOE (the VIX index represents implied annualized daily volatility. The end of month observation is divided by the square root of 12 to translate to monthly volatility); $a_{i,t}$ = the age in months of fund i at time t; $e_{i,t}$ = the annual expense ratio of fund i. Estimation is performed using 2SLS.

Panel A: Equation 5 - Dependent Variable Fund Return				Panel B: Equation 6 - Dependent Variable Fund Flow			
		Coefficient	t-statistic			Coefficient	t-statistic
Constant β_0	β_0	0.0019	19.58	Constant λ_0	λ_0	0.8282	3.38
Flow (fl_{it})	β_1	-0.0009	-16.17	Bottom 5% Dummy (Dbt_{t-1})	λ_1	-1.7373	-5.06
Lagged Flow ($fl_{i,t-1}$)	β_2	0.0003	16.13	Top 5% Dummy (Dtp_{t-1})	λ_2	1.2574	3.31
Lagged Return ($r_{i,t-1}$)	β_3	0.0196	7.90	Return (r_{it})	λ_3	20.3645	15.22
Market Return (m_t)	β_4	0.9775	477.40	Lagged Flow ($fl_{i,t-1}$)	λ_4	0.3857	286.2
Lagged Market Return (m_{t-1})	β_5	0.0602	21.96	Lagged Return ($r_{i,t-1}$)	λ_5	21.1643	18.86
				Dbt_{t-1} x Lagged Return ($Dbt_{t-1}r_{i,t-1}$)	λ_6	-24.8366	-6.83
				Dtp_{t-1} x Lagged Return ($Dtp_{t-1}r_{i,t-1}$)	λ_7	-9.7186	-2.72
				Bond Return (bm_t)	λ_8	0.5503	0.21
				Lagged Bond Return (bm_{t-1})	λ_9	8.4827	3.31
				Lagged Size (s_{t-1})	λ_{10}	0.5516	22.70
				Lagged VIX (v_{t-1})	λ_{11}	-0.2051	-6.36
				Age (a_t)	λ_{12}	-0.0071	-15.55
				Expenses (e_t)	λ_{13}	-0.0165	-3.90
Adjusted R^2			0.1996	Adjusted R^2			0.1581

Table 5: **Estimation Results for Fund Classification Enhanced Model (Model 4)**

This table reports the outcome of estimating the following two-equation model:

$$r_{it} = \beta_0 + \beta_1 fl_{it} + \beta_2 fl_{i,t-1} + \beta_3 r_{i,t-1} + \beta_4 m_t + \beta_5 m_{t-1} + \beta_6 Dio_{t-1} + \beta_7 Dio_{t-1} fl_{it-1} + \beta_8 Dib_{t-1} + \beta_9 Dib_{t-1} fl_{it-1} + \varepsilon_{it} \quad (7)$$

$$fl_{it} = \lambda_0 + \lambda_1 r_{it} + \lambda_2 fl_{i,t-j} + \lambda_3 r_{i,t-j} + \lambda_4 Dio_{t-1} + \lambda_5 Dio_{t-1} r_{i,t-1} + \lambda_6 Dib_{t-1} + \lambda_7 Dib_{t-1} r_{i,t-1} + \lambda_8 bm_t + \lambda_9 bm_{t-j} + \lambda_{10} s_{i,t-j} + \lambda_{11} v_{t-j} + \lambda_{12} a_{i,t} + \lambda_{13} e_{i,t} + \mu_{it} \quad (8)$$

instrumental variables: $fl_{i,t-j}, r_{i,t-j}, m_t, m_{t-1}, bm_t, bm_{t-1}, s_{i,t-j}, v_{t-j}, a_{i,t}, e_{i,t}, Dio_{t-1}, Dio_{t-1} fl_{it-1}, Dio_{t-1} r_{i,t-1}, Dib_{t-1}, Dib_{t-1} fl_{it-1}, Dib_{t-1} r_{i,t-1}$

where r_{it} = return on fund i at time t; fl_{it} = net fund flow to fund i at time t; m_t = return on the market at time t, proxied by S&P 500; Dio_t=1 if the fund is classified as an institional fund only; Dib_t=1 if the fund is classified as both an institional and retail fund; bm_t = return on the bond market at time t; s_{it} = size of fund i at time t measured as log of the net total assets; v_t = volatility index from CBOE (the VIX index represents implied annualized daily volatility. The end of month observation is divided by the square root of 12 to translate to monthly volatility); $a_{i,t}$ = the age in months of fund i at time t; $e_{i,t}$ = the annual expense ratio of fund i. Estimation is performed using 2SLS.

Panel A: Equation 7 - Dependent Variable Fund Return				Panel B: Equation 8 - Dependent Variable Fund Flow			
		Coefficient	t-statistic			Coefficient	t-statistic
Constant β_0	β_0	0.0014	11.39	Constant λ_0	λ_0	0.4284	1.70
Flow (fl_{it})	β_1	-0.0008	-13.60	Return (r_{it})	λ_1	21.0951	15.77
Lagged Flow ($fl_{i,t-1}$)	β_2	0.0004	13.57	Lagged Flow ($fl_{i,t-1}$)	λ_2	0.3853	285.84
Lagged Return ($r_{i.t-1}$)	β_3	0.0153	6.32	Lagged Return ($r_{i.t-1}$)	λ_3	28.1725	20.40
Market Return (m_t)	β_4	0.9765	474.58	Dummy Institutional *(Dio_{t-1})*	λ_4	-0.2278	-1.40
Lagged Market Return (m_{t-1})	β_5	0.0627	23.49	*D Inst x* Lagged Return *($Dio_{t-1}r_{t-1}$)*	λ_5	-22.9844	-8.59
Dummy Institutional *(Dio_{t-1})*	β_6	0.0010	4.47	Dummy Institutional & Retail*(Dib_{t-1})*	λ_6	1.0746	8.73
Dio_{t-1} x Lagged Flow *($Dio_{t-1}fl_{t-1}$)*	β_7	-0.0006	-13.55	*D Inst&R x* lagged return *($Dib_{t-1}r_{t-1}$)*	λ_7	-13.3624	-6.68
Dummy Institutional & Retail *(Dib_{t-1})*	β_8	0.0005	2.91	Bond Return (bm_t)	λ_8	0.9240	0.35
Dib_{t-1} x Lagged Flow *($Dib_{t-1}fl_{t-1}$)*	β_9	0.0001	12.01	Lagged Bond Return (bm_{t-1})	λ_9	8.1450	3.19
				Lagged Size (s_{t-1})	λ_{10}	0.5703	23.44
				Lagged VIX (v_{t-1})	λ_{11}	-0.2068	-6.41
				Age (a_t)	λ_{12}	-0.0071	-15.65
				Expenses (e_t)	λ_{13}	-0.0145	-3.43
Adjusted R^2			0.2574	Adjusted R^2			0.1584

Table 6: Estimation Results for 'New' Fund Enhanced Model (Model 5)

This table reports the outcome of estimating the following two-equation model:

$$r_{it} = \beta_0 + \beta_1 fl_{it} + \beta_2 fl_{i,t-j} + \beta_3 r_{i,t-j} + \beta_4 m_t + \beta_5 m_{t-j} + \beta_6 Dnf_{t-1} + \beta_7 Dnf_{t-1} fl_{it} + \varepsilon_{it} \quad (9)$$

$$fl_{it} = \lambda_0 + \lambda_1 r_{it} + \lambda_2 fl_{i,t-j} + \lambda_3 r_{i,t-j} + \lambda_4 bm_t + \lambda_5 bm_{t-j} + \lambda_6 s_{i,t-j} + \lambda_7 v_{t-j} + \lambda_8 a_{i,t} + \lambda_9 e_{i,t} + \lambda_{10} Dnf_{t-1} + \lambda_{11} Dnf_{t-1} r_{i,t-j} + \mu_{it} \quad (10)$$

instrumental variables: $fl_{i,t-j}, r_{i,t-j}, m_t, m_{t-1}, bm_t, bm_{t-1}, s_{i,t-j}, v_{t-j}, a_{i,t}, e_{i,t}, Dnf_{t-1}, Dnf_{t-1} fl_{i,t-j}, Dnf_{t-1} r_{i,t-j}$

where r_{it} = return on fund i at time t; fl_{it} = net fund flow to fund i at time t; m_t = return on the market at time t, proxied by S&P 500; Dnf_1= 1 if age is ≤ 12 months; bm_t = return on the bond market at time t; s_{it} = size of fund i at time t measured as log of the net total assets; v_t = volatility index from CBOE (the VIX index represents implied annualized daily volatility. The end of month observation is divided by the square root of 12 to translate to monthly volatility); $a_{i,t}$ = the age in months of fund i at time t; $e_{i,t}$ = the annual expense ratio of fund i. Estimation is performed using 2SLS.

Panel A: Equation 9 - Dependent Variable Fund Return				Panel B: Equation 10 - Dependent Variable Fund Flow			
		Coefficient	t-statistic			Coefficient	t-statistic
Constant β_0	β_0	0.0018	19.32	Constant λ_0	λ_0	0.5070	2.03
Flow (fl_{it})	β_1	-0.0007	-14.72	Return (r_{it})	λ_1	20.7075	15.47
Lagged Flow ($fl_{i,t-1}$)	β_2	0.0003	14.70	Lagged Flow ($fl_{i,t-1}$)	λ_2	0.3856	286.04
Lagged Return ($r_{i.t-1}$)	β_3	0.0162	6.86	Lagged Return ($r_{i.t-1}$)	λ_3	20.8718	20.85
Market Return (m_t)	β_4	0.9752	499.43	Bond Return (bm_t)	λ_4	0.7860	0.30
Lagged Market Ret (m_{t-1})	β_5	0.06241	23.92	Lagged Bond Ret (bm_{t-1})	λ_5	8.6390	3.38
Dummy New Fund (Dnf_{t-1})	β_6	-0.0001	-0.38	Lagged Size (s_{t-1})	λ_6	0.5894	23.61
DNF x lagged flow (Dnf_{t-1} x $fl_{i,t-1}$)	β_7	-0.0001	-6.52	Lagged VIX (v_{t-1})	λ_7	-0.1944	-6.03
				Age (a_t)	λ_8	-0.0068	-14.92
				Expenses (e_t)	λ_9	-0.0090	-2.05
				Dummy new fund(Dnf_{t-1})	λ_{10}	1.4377	6.51
				DNF x lagged return (Dnf_{t-1} x $r_{i,t-1}$)	λ_{11}	-13.1454	-4.64
Adjusted R^2			0.273	Adjusted R^2			0.158

Table 7: Estimation Results for Multiple Lags Enhanced Model (Model 6)

This table reports the outcome of estimating the following two-equation model:

$$r_{it} = \beta_0 + \beta_1 fl_{it} + \sum_{j=1}^{6} \beta_{1+j} fl_{i,t-j} + \sum_{j=1}^{6} \beta_{7+j} r_{i,t-j} + \sum_{j=0}^{6} \beta_{14+j} m_{t-j} + \varepsilon_{it} \tag{11}$$

$$fl_{it} = \lambda_0 + \lambda_1 r_{it} + \sum_{i=1}^{6} \lambda_{1+j} r_{i,t-j} + \sum_{j=1}^{6} \lambda_{7+j} fl_{i,t-j} + \sum_{j=0}^{6} \lambda_{14+j} bm_{t-j} + \sum_{i=1}^{6} \lambda_{20+j} s_{i,t-j} + \lambda_{27} v_{t-1} + \lambda_{28} a_{i,t} + \lambda_{29} e_{i,t} + \mu_{it} \tag{12}$$

instrumental variables = $fl_{i,t-j}, r_{i,t-j}, m_t, m_{t-j}, bm_t, bm_{t-j}, s_{i,t-j}, v_{t-1}, a_{i,t}, e_{i,t}$; where j = 1 to 6.

where r_{it} = return on fund i at time t; fl_{it} = net fund flow to fund i at time t; m_t = return on the market at time t, proxied by S&P 500; bm_t = return on the bond market at time t; s_{it} = size of fund i at time t measured as log of the net total assets; v_t = volatility index from CBOE (the VIX index represents implied annualized daily volatility. The end of month observation is divided by the square root of 12 to translate to monthly volatility); $a_{i,t}$ = the age in months of fund i at time t; $e_{i,t}$ = the annual expense ratio of fund i. Estimation is performed using 2SLS.

Panel A: Equation 11 - Dependent Variable Fund Return				Panel B: Equation 12 - Dependent Variable Fund Flow			
		Coefficient	t-statistic			Coefficient	t-statistic
Constant β_0	β_0	0.0009	12.85	Constant λ_0	λ_0	0.0861	0.37
Flow (fl_{it})	β_1	- 0.2940#	-6.90	Return (r_{it})	λ_1	21.0394	16.68
Lagged Flow ($fl_{i,t-1}$)	β_2	0.0476#	6.92	Lagged Return ($r_{i,t-1}$)	λ_2	35.0808	37.56
Lagged Flow ($fl_{i,t-2}$)	β_3	0.0680#	6.08	Lagged Return ($r_{i,t-2}$)	λ_3	17.8388	19.04
Lagged Flow ($fl_{i,t-3}$)	β_4	0.0424#	5.66	Lagged Return ($r_{i,t-3}$)	λ_4	10.7919	11.64
Lagged Flow ($fl_{i,t-4}$)	β_5	0.0209#	5.85	Lagged Return ($r_{i,t-4}$)	λ_5	5.3962	5.89
Lagged Flow ($fl_{i,t-5}$)	β_6	0.0088#	3.74	Lagged Return ($r_{i,t-5}$)	λ_6	4.4115	4.93
Lagged Flow ($fl_{i,t-6}$)	β_7	0.0115#	4.02	Lagged Return ($r_{i,t-6}$)	λ_7	-1.0182	-1.16
Lagged Return ($r_{i,t-1}$)	β_8	0.0141	5.95	Lagged Flow ($fl_{i,t-1}$)	λ_8	0.1607	109.28
Lagged Return ($r_{i,t-2}$)	β_9	0.0255	13.99	Lagged Flow ($fl_{i,t-2}$)	λ_9	0.2616	176.63
Lagged Return ($r_{i,t-3}$)	β_{10}	0.0052	3.30	Lagged Flow ($fl_{i,t-3}$)	λ_{10}	0.1695	111.56
Lagged Return ($r_{i,t-4}$)	β_{11}	0.0565	36.88	Lagged Flow ($fl_{i,t-4}$)	λ_{11}	0.0686	45.31
Lagged Return ($r_{i,t-5}$)	β_{12}	-0.0183	-12.16	Lagged Flow ($fl_{i,t-5}$)	λ_{12}	0.0334	22.80
Lagged Return ($r_{i,t-6}$)	β_{13}	0.1184	79.36	Lagged Flow ($fl_{i,t-6}$)	λ_{13}	0.0520	36.42
Market Return (m_t)	β_{14}	0.9644	564.68	Bond Return (bm_t)	λ_{14}	7.1209	2.79
Lagged Market Ret (m_{t-1})	β_{15}	0.0640	27.03	Lagged Bond Return (bm_{t-1})	λ_{15}	13.7333	5.62
Lagged Market Ret (m_{t-2})	β_{16}	-0.0302	-13.47	Lagged Bond Return (bm_{t-2})	λ_{16}	12.4357	4.90
Lagged Market Ret (m_{t-3})	β_{17}	0.0034	1.66	Lagged Bond Return (bm_{t-3})	λ_{17}	0.6951	0.27
Lagged Market Ret (m_{t-4})	β_{18}	-0.0415	-20.55	Lagged Bond Return (bm_{t-4})	λ_{18}	17.9389	7.14
Lagged Market Ret (m_{t-5})	β_{19}	-0.0282	-14.03	Lagged Bond Return (bm_{t-5})	λ_{19}	8.1744	3.37
Lagged Market Ret (m_{t-6})	β_{20}	-0.0776	-38.64	Lagged Bond Return (bm_{t-6})	λ_{20}	2.6918	1.11
				Lagged Size (s_{t-1})	λ_{21}	-6.4164	-22.16
				Lagged Size (s_{t-2})	λ_{22}	2.1306	5.51
				Lagged Size (s_{t-3})	λ_{23}	2.5385	6.72
				Lagged Size (s_{t-4})	λ_{24}	2.4086	6.65
				Lagged Size (s_{t-5})	λ_{25}	0.5124	1.49
				Lagged Size (s_{t-6})	λ_{26}	-1.1451	-4.79
				Lagged VIX (v_{t-1})	λ_{27}	-0.0350	-1.19
				Age (a_t)	λ_{28}	-0.0023	-5.63
				Expenses (e_t)	λ_{29}	-0.0161	-3.53
Adjusted R^2			0.4965	Adjusted R^2			0.3272

Each of the values have been multiplied by 10^3.

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