U.S. Mutual Fund Flow-Performance Relationship and Its Managerial Implications: An Empirical Investigation

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ABSTRACT

This is an empirical study examining the impact of US mutual fund flow volatility and fee structure on mutual fund flow-performance relationship using data for the period from 1993 to 2006. The purpose of the study is to provide empirical evidence on how investors allocate their investments in response to past performance among funds exhibiting varying volatilities and fee structures. Our results show that mutual funds that adopt moderate risk strategy enjoy the greatest flow-performance sensitivity. Other findings are while direct marketing expense (12b_1 expense item) triggers greater investor response to past performance, the level of front-end and back-end load will not influence the final mutual fund picking decisions. However, if past returns are indecisive, the negative effect of loads will outweigh the positive effect, hence dampening the flow-performance sensitivity. Our results provide an insight into investor behaviour and it has policy implications to managers, whose compensation is positively related to the amount of assets under their management.

Key Words: Mutual funds, fund flows, fund volatility, fund performance

JEL Classification: G12, G23

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1. Introduction

One of the most interesting financial phenomena of the past thirty years is the explosive growth of mutual funds. This is particularly true in the United States where the total number of funds grew from 155 in 1976 to 8606 in 2006, with the total net assets of mutual funds grew from USD $15.8 billion to $9.2 trillion[1]. The fast expansion of mutual funds is attributed to several advantages over investment in individual stocks, including diversification and professional management. When mutual funds become a popular investment choice, one question which arises is what determines investor decision in choosing among thousands of mutual funds?

In relation to this question, substantial studies have been undertaken to analyse the potential determinants of mutual fund flows. The most widely accepted findings are that mutual fund flows are highly influenced by past performance, but in an asymmetric way, namely flow-performance convexity. In other words, the prior superior funds get the lion's share of inflows, while poorly performed funds are not severely disciplined with equally large outflows (Ippolito, 1992; Gruber, 1996; Goetzman and Peles, 1997). Though investors give large weight to past performance, it has been shown that other fund attributes also play important roles in fund selection.

A number of studies have analysed the impact of fund size, reputation, fees, age and other characteristics in relation to mutual fund flows. But few studies have been undertaken to examine how investment funds are allocated in response to performance in the presence of those attributes. Research in this area is important because when investors search for mutual funds they are more likely to compare and select funds that experience similar past returns. Hence, by obtaining an understanding of investor behaviour, managers are able to adjust fund characteristics to invoke larger flows.

This study builds on the convex flow-performance relationship initiated by Ippolito

[1] Data are available from CRSP.

(1992). Specifically, this paper has three objectives. Firstly, we seek to establish how investors react towards different levels of volatility for a given performance of a fund. Secondly, to interpret how different fee structures and how investors interpret these fee structures in relation to fund performance. Lastly, the study will examine the roles that front-end and back-end loads play for a given performance level.

The paper is organized as follows: Section Two provides a review of literature. Section Three consists of a discussion on the data and methodology adopted in this study. Section Four presents the results generated using the methodology outlined in Section Three. The results are discussed and analyzed in relation to the hypotheses and findings of prior studies. Finally, Section Five concludes the paper.

2 Literature Review

There is a substantial body of literature on the mutual fund flow-performance relationship (Ippolito, 1992; Gruber, 1996; Sirri and Tufano, 1998). Existing literature on the relationship provides evidence on investor rationality in interpreting past performance. Investors allocate money disproportionately among good and bad performers. They flock into past winners and respond less sensitively to past losers.

There are three main explanations for this phenomenon. The first view is investors' disbelief of market efficiency. Brown and Goetzmann (1995), Carhart (1997) and Bollen and Busse (2005) documented that a short-term persistence exists in mutual funds although efficient market theory states that past returns give no indication about future returns (Fama, 1970). Consequently, investors tend to use past returns as a guide of future performance (Ippolito, 1992).

The second explanation is pointed out by Goetzmann and Peles (1997) as cognitive dissonance. They argued that this asymmetric behaviour reflects psychological bias of investors who want to justify their past decisions. This irrational behaviour forms an over optimistic expectation of future performance. Consequently, winners are rewarded with large flows while losers are hardly punished (Sawicki, 2001).

The third view suggests that investors believe that poorly performed funds are more likely to experience a change in strategy so that they are willing to stay in badly performed funds. According to Lynch and Musto (2003), fund managers tend to switch to different investments or take riskier assets following bad performance. Building on the Heinkel and Stoughton (1994) argument that funds respond to bad, but not good performance by replacing the personnel or techniques, Khorana (1996) found a significant negative relationship between manager turnover and past performance. Those findings suggested that if a bad performance is likely to be followed by a new strategy, the next period return could be largely improved. As a result, investors have grounds to believe that poor performance won't persist and implicitly be convinced to stay in poor funds.

2.1 Managerial Incentives

Managerial incentives in the presence of the convex flow-performance relationship have been analysed in a number of studies (Chevalier and Ellison, 1997; Busse, 2001; Chen and Pennacchi, 2002). Since manager income arises from an increase in net flows, it encourages them to take excessive risk to increase the value of the compensation (Brown, Harlow and Stark, 1996). Li and Tiwari (2006) used a two risk-neutral manager model to demonstrate that given the unequal performances of the managers at the interim stage, the manager with poor performance tended to increase asset riskiness. The argument is that the call-option-payoff-like [2] flow-performance relationship implies that poorly performed funds need not be penalised by large outflows so that managers are able to exploit such limited-downside-payoff to increase their compensations (Chevalier and Ellison, 1997; Koski and Pontiff, 1999).

Apart from switching to risky assets to get potential larger net flows. Lynch and Musto (2003) found a high absolute loading change after poor performance, which means that managers make redemption more expensive so they can retain investors.

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[2] A call option payoff diagram is convex, which has an unlimited upside payoff and a limited downside payoff. In the presence of the convexity, option value increases when volatility increases.

This finding is consistent with investor psychological behaviour studied by Ivkovic and Weisbenner (2006), who found investors tend to hold the funds long enough to justify the loads. Sigurdsson (2005) pointed out that investors are less willing to sell poorly performed funds unless the expected return from switching to another fund is sufficiently high to compensate the back-end load[3]. There is evidence implying that managers are likely to rely on loads to dissuade redemptions (Chordia, 1996).

2.2 Impact of Fund Attributes on Flow-Performance Convexity

Given managers' incentives to manipulate fund riskiness under the convex flow-performance relationship, studies of investor reactions in response to the risk-taking strategy showed that investors do recognise and account for such incentives when allocating their wealth. Sirri and Tufano (1998) documented a negative relationship between flows and volatility. Huang, Wei and Yan (2006) reported that an increase in volatility will dampen the performance-flow sensitivity. These findings indicate that the potential larger net flows by exploiting the convex flow-performance relationship could be offset by potential smaller net flows due to excessive risk-taking. They also show that investors do not appreciate the good performance which results from an aggressive strategy. Interestingly, Huang, Wei and Yan (2006) found a slightly positive relationship between volatility and flows. They argued that the positive relationship may be due to an optimal portfolio strategy in which active fund[4] managers whose effort is unobservable by the investors, are given incentives to take excessive risks to distinguish them from passive fund[5] managers (Dybvig, Farnsworth and Carpenter, 2003). The mixed findings on the impact of volatility on flows suggest some level of volatility that may be appreciated by investors, and volatility beyond that level will be avoided. While previous studies focus on investor reactions towards the overall level of volatility,

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[3] A back-end load is a fee that investors pay when they sell a mutual fund. This fee usually goes to the mutual fund brokers that sell the fund's shares.

[4] Active funds refer to a portfolio management strategy where the fund managers pick specific investments attempting to outperform a market index.

[5] Passive funds are also called index funds, which are managed to closely track a particular market index.

less effort has been devoted to analysing their responses to different levels of volatility. Therefore, in line with the objectives of this paper we propose the following hypothesis:

H_1: Funds with moderate volatility will have more net flows than either high or low volatility funds in response to performance.

A number of studies found that high total expenses reduce the final return distributed to investors. As a result, investors learn to avoid high expense funds when allocating their money (Gruber, 1996; Gallaher, Kaniel and Starks, 2006). Carhart (1997) conducted a cross-sectional analysis on U.S. open-end equity mutual funds and found that on average, mutual funds do not recoup their investment costs through higher returns. A significant negative coefficient on expense ratio implies that annual excess returns drop with an increase in expense ratio. Chordia (1996) argued that investors are highly sensitive to those in-your-face fees, such as front-end[6], back-end loads and operating costs[7]. Given those fees are regarded as extra burden on investors in terms of either decreasing the amount of original investment or reducing the final returns that are available to the investors, a wise investor would prefer a low charge fund because of cost savings.

While a high overall expense fund tends to have less fund flows, 12b_1[8] expense used for advertising that is included in operating expense ratio, is found to have a positive impact on fund flows. Several studies disaggregated operating expense ratio into 12b_1 fee and other operating expenses to analyse the impact of adverting in relation to fund flows through 12b_1 spending (Jain and Wu, 2000; Barber, Odean and Zheng, 2005; Gallaher, Kaniel and Starks, 2006). Apart from 12b_1 spending, Sirri and Tufano (1998) used loads as a proxy for marketing costs and found a positive relationship between flows and loads. This result is inconsistent with those

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6 Front-end load is a fee that investors pay when they purchase a mutual fund. This fee usually goes to brokers who sell the fund's shares.

7 Operating expenses include management fees, 12b-1, shareholder service expenses and other administrative expenses.

8 12b-1 fees are also called distribution fees, which are paid for advertising, printing of prospectus and brokers compensation. It is included in the operating expenses.

in other studies which argue that loads have a detrimental effect on flows (Chordia, 1996; Wilcox, 2003). Sirri and Tufano (1998) argued that loads are paid to brokers as a sales commission so that high loads will encourage brokers to promote the funds more heavily. Therefore, funds with high advertising effort through 12b_1 spending and/or loads tend to attract more flows.

The above findings in relation to fund charges imply that investors may hold different perceptions towards fee types. In summary, it seems reasonable to assume that the rational investor who is interested in holding an actively managed fund will choose one with a low expense when past returns are similar. Also, 12b-1 expense, pure marketing spending, is likely to attract more flows than a high load since brokers may not successfully persuade investors to purchase a high load fund. On the basis of the above discussion, the following two hypotheses are formulated:

H_2: Funds with higher operating expenses net of 12b-1 expense will have less net flows in response to performance.

H_3: Funds with higher 12b-1 expenses relative to loads will have greater net flows in response to performance.

The above discussion shows there is mixed empirical evidence on the impact of loads on flow-performance sensitivity. On one hand, investors prefer no-load or low load funds since loads add extra burden on investors (Barber, Odean and Zheng, 2005). Hence, the flow-performance sensitivity would be dampened as investors choose a low load fund among the funds with similar past returns. In addition, Ippolito (1992) documented that when back-end load is low, investors are more willing to pull out from funds to realise gains or cut off loses. Therefore, a relatively small load has a tendency to linearise the flow-performance convexity (Sigurdsson, 2005).

On the other hand, high loads are found to strengthen convexity in terms of reducing search costs while dissuading redemption. Firstly, Sirri and Tufano (1998) who argued investors face search costs when shopping for mutual funds suggested that a high load will alleviate such costs through brokers advertising. A high load induces brokers to promote funds more heavily since they will get a higher compensation from each transaction. Sirri and Tufano (1998) also found a marginally significant negative coefficient on decreases in loads, which implies that decreasing loads might reduce flows, as the incentives for salespeople are weakened. Effectively, funds exhibiting high marketing effort by paying more to brokers are more visible to investors. Thereby attracting more flows than funds with less marketing effort given same performance (Jain and Wu, 2000). The second argument is raised by Lynch and Musto (2003) who found a high back-end load retains investors in the funds, especially for poorly performed funds. Sigurdsson (2005) obtained a similar result, that is when cost of exiting is expensive investors are reluctant to pull out their investments and would choose to stay for a longer period to justify the loads. These findings are consistent with manager incentive to dissuade redemption by setting a high exit fee.

The above findings suggest that loads have a two-fold effect on the flow-performance sensitivity. However, the net effect is not well addressed in the existing literature. To provide further evidence in this area, the last two hypotheses are formed as following:

H_4: Funds with higher front-end loads will have greater fund flows in response to performance.

H_5: Funds with higher back-end loads will have greater fund flows in response to performance.

3 Data and Methdology

3.1 Data Description

The data required for this research are sourced from Center for Research in Security Price (CRSP) Survivor-Bias-Free U.S. Mutual Fund Database. Since CRSP does not provide consistent fund investment objectives for the years prior to 1992, the sample covers the period from January 1993 to September 2006 from which we extract data on monthly returns, monthly total net assets, load fees, 12b-1 expense and operating expenses. To calculate risk-adjusted return, monthly market premium size factor, book to market ratio, 1-month T-bill rate and momentum factor are collected from Kenneth French's website.

We follow a procedure similar to those of Barber, Odean and Zheng (2005) and Huang, Wei and Yan (2006) and use the additional information CRSP provides on fund classifications to construct a sample of diversified U.S. open-end equity funds. Comparable with prior literature, this study excludes index funds, sector funds, international funds, money market funds, bond funds and funds with no classification. From the remaining funds, we select funds with the ICDI[9] objective: Aggressive Growth, MidCaps, Growth and Income, Growth, Income Growth and Small Caps. If ICDI objectives are missing, we select funds with Weisenberger codes: G, I, GCI, IEQ, LTG, MCG and SCG[10], which are comparable to the ICDI codes. Finally, we drop funds with sales restrictions.

Tables 1 and 2 present some descriptive statistics of the data. Within the sample period, there are 5241 distinct funds that meet the above selection criteria, with a total of 435,351 observations. They have average total net assets of $387 million dollars. Load funds constitute 78% of the funds, charging a front-end load and a back-end load of 8.98% and 6% respectively. Nearly two-thirds of the funds have a 12b_1 distribution channel to advertise the funds. The spending varies from 0% of the total assets to 1.25%, being the maximum allowable amount. They deliver an average raw return of 0.7%, ranging from -27% to 34%, which on average under-perform the market by 8 basis points per month.

INSERT TABLE 1 HERE

INSERT TABLE 2 HERE

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[9] ICDI represents for Investment Company Data Incorporated.

[10] Weisenberger mutual fund classification is comparable to ICDI code. G, I, GCI, IEQ, LTG, MCG and SCG represents for growth, income, growth and current income, equity income, long-term growth, maximum capital gains and small capitalization growth.

3.2 Methodology

3.2.1 Definitions

3.2.1.1 Net Flows

In line with the literature (Gruber, 1996; Barber, Odean and Zheng, 2005; Huang, Wei and Yan, 2007) mutual fund flows are defined as the net percentage growth of fund assets from the previous month:

$$Flow_{i,t} = \frac{TNA_{i,t} - (1 + r_{i,t})TNA_{i,t-1}}{TNA_{i,t-1}} \tag{1}$$

Where $Flow_{i,t}$ is the net flows of fund i at month t, and it is defined as a net percentage growth in fund assets. $TNA_{i,t}$ denotes fund i's total net assets at the end of month t and $r_{i,t}$ is the raw return of fund i during month t. This definition is based on the assumption that all investor earnings are automatically reinvested in the funds. Hence, $Flow_{i,t}$ represents the percentage growth of a fund in excess of the growth that would have occurred as if all returns have been reinvested.

3.2.1.2 Fund Volatility/Riskiness

Following Ippolito (1992) and Sirri and Tufano (1998), funds' riskiness is reported in terms of its total risk rather than the portfolio beta. The rationale is that fund beta only captures the systematic portion of the risk exposures. But the standard deviation of historical returns incorporates the total risk that investors will consider when they choose the fund so that it will give a better approximation of fund volatility. Therefore, fund volatility is measured as the standard deviation of monthly raw returns in the 12-month prior to each month t.

$$\sigma_{i,t} = \sqrt{\frac{\sum_{t=1}^{12} (r_{i,t} - \mu_{i,t})^2}{12}} \tag{2}$$

Where $\sigma_{i,t}$ is the standard deviation of fund i for the month t that measures the volatility of fund i's return for the 12-month prior to month t; $r_{i,t}$ is the monthly raw return of fund i during the previous 12 months; and $\mu_{i,t}$ is the average raw return of fund i for the previous 12 months.

3.2.1.3 Excess Return Measure

To compute mutual fund performance the momentum factor model of Jegadeesh and Titman (1993) is utilised. This model was developed in response to Fama and French's (1993) 3-factor model's inability to explain cross-sectional variation in momentum-sorted portfolio returns. The inclusion of the momentum factor in the model has been shown in various contexts to provide explanatory power for the observed cross-sectional variation in fund performance (Carhart, 1997; Chen, Hong, Huang and Kubik, 2004). Therefore, the excess return is measured using Carhart (1997) four factor model, which is specified as follows:

$$r_{i,t} - r_{rf,t} = \alpha_i + \beta_{1i}(r_{m,t} - r_{rf,t}) + \beta_{2i}S_t + \beta_{3i}H_t + \beta_{4i}M_t + \varepsilon_{i,t} \tag{3}$$

Where $r_{i,t}$ is the raw return of fund i at month t; and $r_{rf,t}$ is the one month T-bill rate at time t; α_i is the risk adjusted return of fund i; $r_{m,t} - r_{rf,t}$ is the excess return of the market (S&P 500) over the one-month T-bill rate at time t; S_t, H_t and M_t denote the size factor, the book to market factor and momentum factor at time t respectively.

3.2.2 Multivariable Testing

To test hypotheses 1 to 3 we will, firstly, replicate the results of Ippolito (1992) by examining the fund net flows for each performance rank to pinpoint the flow-performance convexity. In addition, a series of regressions are constructed to estimate the impact of various determinants on fund flow-performance convexity (Huang, Wei and Yan, 2006). Piecewise linear regression will be employed to capture the non-linear flow-performance relationship.

3.2.2.1 Testing the Overall Impact of Volatility and Fees on Flow-Performance Sensitivity

Previous literature has documented that mutual fund flows react to past performance in an asymmetric way, meaning the flow-performance sensitivity is larger for funds with good performance compared with badly performing funds. To incorporate this convex flow-performance relationship, we follow Sirri and Tufano's (1998) methodology to rank funds into 5 quintiles. Each month, performance ranks ranging from 0 to 1 are assigned to funds to their raw return during the past 12 month. The rank for funds in the bottom performance quintile (PL) is defined as Min ($Rank_{t-1}$, 0.2). Funds in the three medium performance quintiles (PM) are grouped together and receive ranks that are defined as Min (0.6, $Rank_{t-1}$ – PL). The rank for the top performance quintile (PH) is defined as Max (0, $Rank_{t-1}$ – 0.8). The coefficients on these piecewise decompositions of fractional ranks represent the slope of the flow-performance relationship over the range of sensitivity.

After incorporating the asymmetric flow-performance relation, the influences of volatility and fees on net flows can be measured by regressing fund net flows on the explanatory variables. In addition, Chavalier and Ellison (1997), Bergstresser and Poterba (2002) and Boudoukh, Richardson, Stanton and Whitelaw (2003) found that fund age has a significant impact on flow-performance sensitivity. Hence, we will include Log (Age) as a control variable. We also take Log (Size) as another control variable to adjust the scaling effect of size on percentage fund growth (Jain and Wu, 2000; Kempf and Ruenzi, 2003; Gallaher, Kaniel and Starks, 2006). The model is specified as follows:

$$\begin{aligned} Flow_{i,t} &= a + \beta_1 V_{i,t} + \beta_2 TE_{i,t-1} + \beta_3 FL_{i,t-1} + \beta_4 BL_{i,t-1} + \beta_5 B_{i,t-1} \\ &\quad + \beta_6 Log\,(TNA_{i,t-1}) + \beta_7 Log\,(Age_{i,t-1}) \\ &\quad + \beta_8 PH_{i,t-1} + \beta_9 PM_{i,t-1} + \beta_{10} PL_{i,t-1} + \varepsilon_{i,t} \end{aligned} \tag{4}$$

The variables are defined as:

$Flow_{i,t}$: Net flows into fund i at month t calculated from equation 3.1

$PH_{i,t-1}, PM_{i,t-1}, PL_{i,t-1}$: Performance quintiles, each quintile includes funds with the corresponding past returns, which are defined in 3.3.3.1

$V_{i,t}$: Volatility of fund i's performance over last 12 months obtained from equation 3.2.

$TE_{i,t-1}$: Fund i's expense ratio that is the ratio of total investment that shareholders pay for the fund's operating expenses at time $t-1$

$FL_{i,t-1}$: Fund i's front-end load at time $t-1$

$BL_{i,t-1}$: Fund i's back-end load at time $t-1$

$B_{i,t-1}$: Fund i's 12b-1 expense at time $t-1$

$Log(TNA_{i,t-1})$: Control variable, logarithm of fund i's size at time $t-1$

$Log(Age_{i,t-1})$: Control variable, logarithm of fund i's age at time $t-1$

Coefficients β_1, β_2, β_3, β_4 and β_5 will tell the average relationship between fund attributes and fund flows. While coefficients β_8, β_9 and β_{10} will show the sensitivity of how fund flows respond to past performance.

3.2.2.2 Testing the Interaction between Performance and Volatility

To test *H₁*, that funds with moderate volatility will have greater flow-performance sensitivity than either high or low volatility funds, we first rank the funds based on their riskiness $\sigma_{i,t}$ calculated from equation 2. Each month, funds are pooled into 3 volatility ranks, which are VH, VM and VL. VH includes the top one-third funds with the most volatile performance and VL consists of the bottom one-third funds that are least volatile. The medium volatile funds are grouped into VM. The volatility rank takes a value of 1 if the fund is in that rank, otherwise it equals to 0.

The impact of volatility on the flow-performance sensitivity is tested by including an interaction term between volatility, performance and volatility rank dummies. The interaction terms allow separate examination of the extent to which volatility dampens or strengthens the flow-performance sensitivity in the three volatility ranks. The modified regression is specified as follows:

$$\begin{aligned} Flow_{i,t} &= a + \beta_1 V_{i,t} + \beta_2 TE_{i,t-1} + \beta_3 FL_{i,t-1} + \beta_4 BL_{i,t-1} + \beta_5 B_{i,t-1} \\ &\quad + \beta_5 Log(TNA_{i,t-1}) + \beta_7 Log(Age_{i,t-1}) \\ &\quad + \beta_8 PH_{i,t-1} + \beta_9 PM_{i,t-1} + \beta_{10} PL_{i,t-1} + \varepsilon_{i,t} \\ &\quad + \beta_{11} V_{i,t} P_{i,t-1} VH_{i,t-1} + \beta_{12} V_{i,t} P_{i,t-1} VM_{i,t-1} + \beta_{13} V_{i,t} P_{i,t-1} VL_{i,t-1} + \varepsilon_{i,t} \end{aligned} \tag{5}$$

The variables are defined as follows:

$Flow_{i,t}$, $PH_{i,t-1}, PM_{i,t-1}, PL_{i,t-1}$, $V_{i,t}$, $TE_{i,t-1}$, $FL_{i,t-1}$, $BL_{i,t-1}$, $B_{i,t-1}$, $Log(TNA_{i,t-1})$ and $Log(Age_{i,t-1})$ are the same definitions given in earlier.

$P_{i,t-1}$:	fund i's excess return at time $t-1$ that obtained from equation 3.
VH, VM and VL:	volatility rank dummies. The rank equals to 1 if fund i's volatility fall in that rank, otherwise equal to 0.

Coefficients β_{11}, β_{12} and β_{13} indicate both the direction and magnitude of how different levels of volatility change the flow-performance sensitivity.

3.2.2.3 Testing the Interaction between Performance and Fees

To test H_2 to H_5, how different types of fees affect fund flow-performance sensitivity, equation 5 will be augmented by adding four more independent variables. These are interactions between performance and front-end load, back-end load, 12b_1 expense and operating expenses net of 12b_1 expense. The modified regression is specified as follows:

$$\begin{aligned} Flow_{i,t} &= a + \beta_1 V_{i,t} + \beta_2 TE_{i,t-1} + \beta_3 FL_{i,t-1} + \beta_4 BL_{i,t-1} + \beta_5 B_{i,t-1} \\ &+ \beta_5 Log(TNA_{i,t-1}) + \beta_7 Log(Age_{i,t-1}) \\ &+ \beta_8 PH_{i,t-1} + \beta_9 PM_{i,t-1} + \beta_{10} PL_{i,t-1} \\ &+ \beta_{11} V_{i,t} P_{i,t-1} VH_{i,t-1} + \beta_{12} V_{i,t} P_{i,t-1} VM_{i,t-1} + \beta_{13} V_{i,t} P_{i,t-1} VL_{i,t-1} \\ &+ \beta_n P_{i,t-1} FEE_{i,t-1} + \varepsilon_{i,t} \end{aligned} \tag{6}$$

The variables are defined as follows:

$Flow_{i,t}$, $PH_{i,t-1}, PM_{i,t-1}, PL_{i,t-1}$, $V_{i,t}$, $TE_{i,t-1}$, $FL_{i,t-1}$, $BL_{i,t-1}$, $B_{i,t-1}$, $Log(TNA_{i,t-1})$ $Log(Age_{i,t-1})$, $P_{i,t-1}$, VH, VM and VL are the same definitions as given in equations 4 and 5.

$FEE_{i,t-1}$: Fund i 's fee charges, including front-end load $FL_{i,t-1}$, back-end load $BL_{i,t-1}$, pure operating expenses $O_{i,t-1}$ and 12b_1 expense $B_{i,t-1}$, which are interacted with fund i 's excess performance $t-1$ in turn.

Coefficients β_n on the interaction terms show how different types of fees affect the flow-performance sensitivity. A positive coefficient implies that this type of fee will strengthen the flow-performance. The magnitude of two coefficients will reveal the relative impact of the two expenses on the sensitivity.

4 Results and Discussion

4.1 Preliminary Experimentations

From Table 3, positive coefficients on the high performance, middle performance and low performance ranks with an increase in values agree with previous findings that net flows are positively related to historical performance. This is especially so for the highest-performing funds. This asymmetric investor response to past performance is the flow-performance convexity. The coefficient on PH is 0.729 compared with much smaller values on PM (0.292) and PL (0.053), suggesting that the top funds enjoy at least double the net flows on average than the middle and bottom funds. However, when the top and bottom performance ranks are widened to 33% instead of 20% (Table 4), the convexity is less obvious as evidenced by a smaller β_8 (PH) and a larger β_{10} (PL). Consistent results are found when raw return is used, which are reported in Column B in Tables 3 and 4. The changing sensitivity is summarised in Figures 1 and 2. As we can see the curvature for the flow-performance relationship is greater when a "20, 80, 20" ranking is used, which indicates that the asymmetric response to performance is more apparent at either the two extremes.

The coefficient on fund size as shown in Column A and B for both Tables 3 and 4 is negative and highly significant. Statistically, for large funds, they need to attract more investments to generate a similar increase as small funds can since the returns are specified in percentage term. Different signs on four types of fees (total expenses, front-end load, back-end load and 12b_1 expense) imply different roles played by each charge. When front-end load and 12b_1 expense have a significant positive impact on flows, back-end load and total expense tend to drag down the flows. Another interesting finding is a statistically insignificant coefficient on fund volatility. The sign of the coefficient switches from negative (-0.009) to positive (0.028) when raw return is used instead of excess return. Since existing findings on volatility are fragile (Sirri and Tufano, 1998; Huang, Wei and Yan, 2006), a plausible explanation could be an offsetting effect of volatility resulting from an over-aggregation of data. Thus, to obtain a deeper grasp of the impact of fund volatility and fees on the flow-performance relationship, we segregate volatility levels and fee types and undertake a more detailed analysis in the following sections.

INSERT TABLES 3 and 4 HERE

4.2 Results

The previous section examined the statistical features of the flow-performance relationship that is convex, and also showed that fund volatility provides a weak explanation of net flows. We now focus on the testable hypothesis developed in the literature review. We begin by testing $H_{1:}$ 'Funds with moderate volatility will have stronger flow-performance sensitivity than either high or low volatility funds.'

Table 5 reports the results of the piecewise linear regression of net flows on past performance and the interaction terms between performance, volatility and its volatility ranking, after controlling for fund's size, age, fee charges and riskiness. The results show that net flows react less sensitively to performance for funds experiencing high return volatility, as reflected by the negative statistically significant coefficient on the interaction variable V*P*VH. If the volatility of performance in the past 12 months increases by 1%, the sensitivity of net flows to performance will be reduced by 2.198%. We observe a similar dampening effect on sensitivity for funds experiencing low volatility V*P*VL, but the magnitude is not as large as highly volatile funds. In contrast, volatility doesn't have explanatory power for changes in convexity among middle volatile funds as the coefficient on V*P*VM is statistically insignificant. When raw return is used instead of risk-adjusted return, the divergence in coefficients is more evident as reported in Column B. The coefficient for V*P*VH is negative while middle (V*P*VM) and low (V*P*VL) ranks switch to positive. However, there is no sufficient evidence to infer that volatility will strengthen the convexity because the later two coefficients are statistically insignificant.

INSERT TABLE 5 HERE

Though the results support the hypothesis that funds with moderate volatility enjoy the strongest flow-performance sensitivity, they provide little indication about the volatility boundary around which funds are aiming to target in order to enhance the flow-performance curvature. Thus, we re-rank the funds using different grouping deciles. The new high (low) ranks consist of 20% highest (lowest) volatility funds and the middle 60% fall within middle rank. The reason for narrowing both top and bottom deciles are to find a rough volatility threshold that has stronger flow-performance sensitivity.

Table 6 shows, when volatility range of high rank funds is narrowed from 33% to

20%, the coefficient on V*P*VH declined to -2.206 from -2.198 (refer to Table 5), which suggests that the dampening effect becomes stronger for highly volatile funds. Likewise, a higher negative coefficient is obtained for low volatility funds V*P*VL, -1.816 compared with -1.526 (refer to Table 3). Though the magnitude on middle funds V*P*VM increased from -1.388 to -0.083 (refer to Table 5), it remains insignificant. A larger dampening effect on two ends suggests that volatility has a tendency to linearise the curvature among funds with either extremely high or low return fluctuation. This finding is consistent with Dybvig, Farnsworth and Carpenter (2003) optimal incentive contract argument, which argued that investors appreciate some riskiness taken by managers so that they could earn a higher expected return than they would otherwise get from passively managed funds. It also confirms investor risk reversion argument where investors attempt to avoid risky funds. The extent to which flow-performance sensitivity will be changed are summarised in Figures 3 and 4 when excess return is used. The changes in the curvature of the flow-performance relationships are much smaller for the first ranking (33%, 34%, 33%) compared with the second ranking (20%, 80%, 20%) since the sensitivity lines are much closer for the first one. The blue lines that represent the flow-performance sensitivity for moderate volatility funds exhibit the greatest curvature in both figures.

INSERT TABLE 6 HERE

The results on volatility support the first hypothesis. Given investors respond disproportionately to past performance, volatility will weaken the asymmetric relationship among funds that undergo either extreme low or high riskiness. In contrast, funds with moderate volatility have a more sensitive investor reaction to past performance. When both top and bottom ranks are shortened from 33% to 20%, the weakening effect is magnified. Moreover, when the middle rank comprises a wider range of riskiness, the effect is still insignificant. Although the precise cut-off point of optimal level of volatility can not be identified, we are able to draw a rough volatility range within which it attracts maximum investor funds in response to past performance. That is, moderate return fluctuation around middle 30 percentage will give mutual funds the strongest flow-performance sensitivity.

Several studies have documented that net flows are negatively related to total expense ratio (Gruber, 1996; Carhart, 1997). It is sensible for investors to eschew the purchase of funds with high operating expenses. However, the finding only suggests that investors are putting relatively less money into high fees funds over time and has little indication about how investors respond to performance when funds exhibit different fee structures. In addition, since total expense ratio (TE) comprises pure operating expenses and 12b_1 expense that are used for advertising, the coefficient on TE represents the net effect of the two as evidenced by a 5% significance of the t-statistics in Table 3 for both excess and raw return. Therefore, to examine the individual impact on flow-performance sensitivity, we disaggregate pure operating costs from 12b_1 charge and interact with performance to test the second hypothesis.

The results are presented in Table 5. While the signs of the coefficients on TE and 12b_1 expense and their statistical significance remain same as the significance reported in Table 3, a negative insignificant coefficient on the O*P in Column A is obtained. The result suggests that the level of pure operating expenditure (O*P) does not have statistical power in determining the flow-performance sensitivity. When raw return is used in Column B, the coefficient remains insignificant. Although ostensibly at odds with rational investor behaviour, the result is not surprising as the returns are calculated after deducting all expenses. That is, the returns investors use to make investment decisions have already incorporated the costs.

Grossman and Stiglitz (1980) and Malkiel (1995) theorised that traders searching for superior information earn abnormal returns that just offset the fees they incur. In a delegated fund manager context, this implies that the risk-adjusted return of a portfolio should on average offset the information-gathering costs. Given the strong explanatory power of total expense on net flows, as evidenced for both excess and raw return in Table 5, our findings support the argument. When future return is uncertain, investors are inclined to consider the expense side to minimize their potential outgoings charged by the funds. But, as investors normally rely on past returns as proxy for future performance (Ippolito, 1992), the expense may not play a critical role in determining the flow-performance sensitivity because return itself would be a good indication about the overall return. The above argument provides a theoretical support to the statistically significant result on TE and statistically insignificant result on O*P.

In summary, the results from above analysis do not support the second hypothesis. *Prima facie* the finding is contrary of the argument that operating costs will bring about a decline in the net flows.. As we put the results together, it does provide economic explanation of the role played by expenses with respect to flows and flow-performance sensitivity. Presumably investors avoid high expense funds. However, such avoidance is less evident when past performance is taken into account as investors' primary concern. Therefore, the level of operating expense does not seem to serve a role in determining the flow-performance sensitivity.

Based on earlier findings, the economic role of advertising in consumer choice decisions may lead to greater net flows. With regard to mutual fund advertising literature in particular, both 12b_1 and loads[11] are found to have a potential to increase fund flows (Sirri and Tufano, 1998; Gallaher, Kaniel and Starks, 2006). However, the relative magnitude is unclear. To compare the magnitude of impact, hypothesis three 'Funds with higher 12b_1 expense relative to loads will have greater net flows in response to performance.' will be tested.

We first consider the results for the entire sample of funds. In Table 5, the coefficients on B*P are highly significant regardless of which measurement we use for performance, but they differ much in magnitude with value of 12.335 for excess

[11] They use a sum of front-end load and back-end load as a proxy of marketing. In fact, a high back-end load may probably increases the redemption, hence decreases the net flows. Therefore, we include both front-end load and back-end load as separate independent variable

return and 10.521 for raw return. In contrast, funds with high front-end load tend to have less convex flow-performance sensitivity, implied by a significantly negative coefficient (-1.952). Though front-end load on average serves a positive role in bringing investments, it doesn't add extra positive impact on the convexity. With 1% extra expenditure on advertising, the sensitivity will be strengthened by 12.335% if the funds directly target the investors, but dampened by roughly 1.952% if the funds use brokers as an intermediary. Thus, it appears that on average 12b_1 spending will be a more effective marketing channel than paying brokers to attract potential investments. But, one should consider that some funds are not allowed to charge front-end load and/or 12b_1 expense so that the results that are based on the entire sample could be over-aggregated. To ensure that the results are not distorted by such restrictions, we investigate the different sample funds based on their fee characteristics.

To do so, we separately analyse three subgroups and report the results in Table 7, which consists both load and 12b_1 allowable funds (Column B), non-load funds (Column C) and non-12b_1 funds (Column D). We observe for load and 12b_1 allowable funds, the coefficient on B*P is 12.337 and statistically significant at 1% while the coefficient on FL*P is -1.950 and statistically significant at 1%. The results suggest that 12b_1 plays a positive role in strengthening investor reaction towards past performance as opposed to front-end load that weakens sensitivity. The findings also imply that if a fund is subject to certain marketing restrictions, it would achieve a stronger investor response if all advertising is directly targeting the public. Otherwise, increasing the commission paid to the brokers would partially offset the positive effort made by 12b_1 expense.

Among non-load funds, B*P remains positive and statistically significant at 1% (Column C, Table 7). For those funds who cannot charge load fees, 12b_1 is the only mean to advertise the funds. More important, the strengthening effect is about 5.333% higher than funds that are 12b_1 and load allowable, with the coefficients equal to 17.668% and 12.335% respectively. Among non-12b_1 funds, which have to rely on broker promotion to increase their publicity, appear not to enjoy the benefits brought by the brokers. A positive insignificant coefficient on FL*P in Column D suggests that front-end load doesn't provide statistical explanation in determining the flow-performance relation. In other words, a high marketing effort through brokers may not necessarily get rewarded by greater investor response.

As both load fees and 12b_1 expense are spent in the manner that the managers believe will attract fund flows, the results differ pretty much. 12b_1 expense as anticipated has strong strengthening effect on the sensitivity, especially among non-load funds. Front-end load, despite its significant positive impact on net flows given the coefficient on FL is 0.042 in Column A, Table 7, it only means on average funds with heavy broker promotion tend to have greater investments. And it fails to induce investor response to performance Overall, the third hypothesis can be supported, that is 12b_1 expense has a stronger marketing effect than front-end load in the sense of enhancing the flow-performance sensitivity.

In the preceding discussion, the marketing effect of front-end load on flow-performance sensitivity remains unclear. In the literature of front-end load, Sirri and Tufano (1998) found a positive impact of front-end load on net flows. Other studies, for example Barber, Odean and Zheng (2005) and Sigurdsson (2005) documented a negative impact on net flows. They argued that front-end load is an extra burden levied on investors that is explicitly quoted in the fund prospectus.

The inconsistent findings could be due to the positive effects from marketing being at least partially offset by the negative effects of loads which are salient to investors. To analyse the two-fold effect of front-end load, hypothesis four is tested.

The Column A in Table 8 is extracted from Column A in 4.3, which examines the overall impact on the entire sample. The coefficient on FL*P is negative and statistically significant at 1%. That is, funds with high level of front-end load will have a flatter flow-performance relationship. As investors observe a high entry fee, their decisions would be less driven by performance. However, it is not necessarily the case that high entry charge will weaken their propensity to chase past performance. Capon, Fitzsimons and Weingarten (1994) pointed out that investors would pay less attention to the fees when the magnitude of past returns is sufficiently convincible to dominate the investment decisions. Therefore, to provide a detailed analysis, we will separately analyse funds according to their performance ranks and see how front-end load affects the convexity within each rank.

Table 8 (columns B, C and D) reports the results for high performance, middle performance and low performance funds. For both high and low performed funds, the coefficients on FL*P are insignificant, which provide direct evidence on investor decision preference. If the past return is sufficiently high, the net influence of front-end load will be abated either through a weakening marketing effect or less concern about an upfront charge. Likewise, when funds experienced hardship, investors will show their blunt reaction to past returns. In contrast, middle performed funds will suffer a less curving flow-performance relationship. In Column C, a negative coefficient -1.070 on FL*P suggests that funds with inconspicuous past performance will loss 1.070% of investor response if front-end load increases 1%. That is, the extra burden that investor foresee outweigh the positive side coming from broker promotion.

Evidently, the advertising function served by brokers does not enable the funds to enjoy a more sensitive flow-performance relation. Especially for moderate performed funds, when past returns give investors less indication about future prospects, the negative side of front-end load seems to play a dominant role. However, one thing remains unclear, which is whether the insignificant impact of front-end load among high return and low return funds is due to the offsetting of both significant marketing and fee effects, or neither of them serves an important role. Nevertheless, the net result is sufficient to show the overall important role performed by front-end load.

We now focus on the last hypothesis five dealing with the impact of high back end loads on fund-flow performance. In Table 8 column A, the significant negative coefficient estimates for BL*P with value of -3.073 and t-statistics -2.932 clearly indicates that among all funds with one percentage increase in back-end load will on average dampen the flow-performance sensitivity by 3.073%. The significance changes when we test sub-samples based on fund performance ranks. Like front-end load, the influence of back-end load lessens for both well and poorly performed funds as evidence by statistically insignificant coefficients on BL*P in Columns B and D. But the coefficient remains significantly negative for middle performed funds referring to Column C. These findings are not in line with the literature on agency studies, which argue that managers tend to charge high back-end load to dissuade redemption so that a positive coefficient on BL*P was expected. Nevertheless, we could place a similar argument as we previously made on front-end load, which states investors are less concerned about fees because their decisions are more performance-driven. However, an important distinction should be made between front-end and back-end load. That is, while front-end load mainly determines the level of investment inflows, back-end load not only influences inflows but also redemption in most situations.

Ivkovic and Weisbenner (2006) documented that when a high back-end load may successfully retain the funds, but it may drive investors away at first as they are aware of a future burden levied on them. Evidenced by negative coefficient on middle funds BL*P in Column C, Table 8, investors may not delay their redemption decisions based on the level of exiting charge since the realised return is negligible. In contrast, a high back-end load will make investors eschew the funds and hence reduce the inflows. Therefore, the net impact of back-end load on the flow-performance sensitivity is negative for middle performed funds. However, the situation is slightly different for well performed and badly performed funds. Prospect theory states that most investors are reluctant to realise losses but quickly sell winners. Behavioural finance theory provides some economic support to the insignificant results obtained on BL*P in Column B and D. When funds experience extremely high past return, a high back-end load cannot successfully retard the funds as investors are more likely to realised gains. Similarly, when funds generate extremely low past return, a high back-end load may not add additional impact on investors' redemption decisions because they will hold the shares anyway.

5 Conclusion

The US mutual fund markets have experienced a rapid growth in past two decades. Extensive studies have been undertaken to analyse investor behaviour in relation to their investment decision making where evidence is provided that investors irrationally flock into funds with high past returns and are less sensitive to inferior funds, giving rise to the phenomenon of flow-performance convexity. While most studies focus on the flow-performance relation, few analyse the dynamics of the relationship allowing for dependence of other fund attributes. This study seeks to fill this gap.

The study considered a number of hypotheses. The first deals with evidence on the flow-performance sensitivity among funds, with differing risk profiles. Our tests indicate that investors respond negatively to volatility within high and low volatility ranks, but remain indifferent for funds with moderate risk. When the managed assets consist of extreme risky portfolios or almost risk free investments, investors will react with less sensitivity to the past performance. These findings support the first hypothesis that funds with mild volatility enjoy the strongest flow-performance sensitivity.

The second hypothesis in our study is not supported since we found that the level of operating expenditure doesn't provide statistical explanation on the convexity. Though several studies show a negative relationship between expenses and fund flows, our result is not without its economic justification. Since the return has already incorporated the operating expenses, investors are less likely to consider the expense level as long as high spending can be recouped by high returns.

The third hypothesis compares the effectiveness of two advertising channels used by mutual funds. 12b_1 expense that directly targets the investor is found to have a stronger impact on the convexity than front-end load that is paid to brokers to advertise funds. Especially for 12b_1 only funds, the impact becomes much stronger. In contrast, funds that are not allowed to have 12_1 expense and solely rely on front-end load do not benefit from heavy broker promotion.

The fourth hypothesis examines the net impact of front-end load, given it potentially enhances sensitivity due to the marketing effects or dampening sensitivity because investors view it as an extra burden. The results vary among funds, which largely depend on the level of past returns. When funds experience high or low performance, the net impact is statistically insignificant. But a negative relation is found for middle performance funds. This phenomenon reinforces investor performance chasing behaviour. When past returns are substantially high or low, their decisions are less influenced by front-end load. When past returns give little indication about future prospects, front-end load will dampen their response to the performance, which means the negative effect outweighs the positive effect.

The fifth hypothesis tests the net impact of back-end load, given a high load may retard redemption or stop investors at the first place. The results show that back-end load will on average weaken investor response to past performance, and the dampening effect is more evident for middle performing funds. And the flow-performance sensitivity doesn’t undergo major changes among good and poor funds.

A number of implications can be drawn from our study for fund managers. In general, the convex shape of flow-performance relation makes the manager engage in excessive risk taking. However, our results imply that managers should invest in moderate volatile portfolios. In addition, our results on mutual fund fees suggest that managers may not need to concern much about operating-related fees as long as the expenditure can be justified by a substantial return. Furthermore, it seems managers should reduce both front-end and back-end load. Though loads do not affect the flow-performance sensitivity when past performance is sufficiently high or low, they do dampen investor response when performance is midway. As front-end load cannot successfully attract the investors, nor back-end load can retard the redemption, it seems logical that managers should avoid them. Finally, our results suggest that the best way for mutual fund advertising is through its direct distribution channel, which is through its 12b_1 channel.

One extension to this study is to include more potential explanatory variables. Secondly, in order to find a more accurate cut-off of the optimal volatility range, more volatility ranking combinations may be employed. By doing so, it will not only generate a more precise optimal volatility threshold but also can provide an understanding of the dynamics of the volatility-sensitivity relationship. Moreover, the results on load only show the net impact on flows and do not provide information on how they affect the inflows and outflows separately. Therefore, a more detailed analysis can be conducted to test for the impact of load on both inflows and outflows separately.

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Table 1: Summary Statistics of the Sample U.S. Open-End Equity Mutual Funds during 1993-2006, Source: CRSP

Panel A: Funds Sorted by Styles

Fund Style	No. of Funds
AGG (Aggressive Growth)	282
GMC (Mid Caps)	692
GRI (Growth and Income)	1009
GRO (Growth)	1900
ING (Income and Growth)	222
SCG (Small Companies)	1136
Total	5241

Panel B: Funds Sorted by Fee Structure

No. of Funds	12b_1 Allowable	12b_1 Non-Allowable	Total
Load	3141	1404	4545
Non-Load	263	433	696
Total	3404	1837	5241

Table 2: Cross-Sectional Characteristics of the Sample U.S. Open-End Equity Mutual Funds during 1993-2006

	Minimum	Maximum	Median	Mean
Total Net Assets (m)	0.001	18,224	57	387
Monthly Net Flows	-7%	12%	0.04%	2.4%
Volatility	0.16%	27.15%	4%	4.5%
Raw Return	-27%	34%	0.9%	0.7%
Excess Return	-15%	20%	-1.7%	-1.8%
Expense Ratio	0.01%	9.5%	1.41%	1.5%
12b-1 Expense	0%	1.25%	0.25%	0.4%
Front-End Load	0%	8.98%	0%	1.3%
Back-End Load	0%	6%	0%	1%

Table 3: Effects of Fund Performance, Volatility and Expenses on Fund Net flows

This table reports the effects of fund performance, volatility, and expense on fund net flows. Piecewise linear regression is performed by regressing monthly fund net flows on the standard deviation of raw return of prior 12 months, front-end load, back-end load, total expenses, 12b_1 expense and performance ranks. Each month, performance rank is normalized from 0 to 1. The bottom quintile PL is defined as Min ($Rank_{t-1}$, 0.2) the middle quintile is defined as Min (0.6, $Rank_{t-1}$ − PL), and the highest quintile (PH) is defined as Max (0, $Rank_{t-1}$ − 0.8). The control variables include the lagged logarithmic value of fund age and logarithmic value of fund size (refer to Equation 3.4). Column (A) uses excess return calculated by Carhart four-factor model as a measure of fund performance. Column (B) uses raw return as a measure of performance. t-statistics (in parentheses) calculated with Newey-West robust standard errors are reported. *, ** and *** denote significance at 10%, 5% and 1% levels, respectively.

	A	B
Variable	Excess Return	Raw Return
C	0.071***	0.068***
	(19.672)	(18.907)
V	-0.009	0.028
	(-0.247)	(0.771)
FL	0.045***	0.046***
	(2.740)	(2.787)
BL	-0.185***	-0.188***
	(-5.537)	(-5.610)
TE	-0.390**	-0.414***
	(-1.967)	(-2.013)
12B_1	0.632***	0.648***
	(2.719)	(2.724)
LOG(TNA)	-0.005***	-0.005***
	(-16.247)	(-16.207)
LOG(AGE)	-0.020***	-0.020***
	(-35.373)	(-35.453)
PH	0.729***	0.165***
	(11.059)	(8.246)
PM	0.292***	0.143***
	(21.072)	(21.060)
PL	0.053**	0.005
	(1.9654)	(0.332)
Adj. R^2	0.022	0.021

Table 4: Effects of Fund Performance, Volatility and Expenses on Fund Net Flows

This table reports the effects of fund performance, volatility, and expense on fund net flows. Piecewise linear regression is performed by regressing monthly fund net flows on the standard deviation of raw return of prior 12 months, front-end load, back-end load, total expenses, 12b_1 expense and performance ranks. Each month, performance rank is normalized from 0 to 1. The bottom quintile PL is defined as Min ($Rank_{t-1}$, 0.33) the middle quintile is defined as Min (0.34, $Rank_{t-1}$ – PL), and the highest quintile (PH) is defined as Max (0, $Rank_{t-1}$ – 067.). The control variables include the lagged logarithmic value of fund age and logarithmic value of fund size (refer to Equation 3.4). Column (A) uses excess return calculated by Carhart four-factor model as a measure of fund performance. Column (B) uses raw return as a measure of performance. T-statistics (in parentheses) calculated with Newey-West robust standard errors are reported. *, ** and *** denote significance at 10%, 5% and 1% levels, respectively.

Variable	A Excess Return	B Raw Return
C	0.070***	0.068***
	(19.506)	(18.722)
V	-0.002	0.049
	(-0.069)	(1.411)
FL	0.045***	0.047***
	(2.752)	(2.851)
BL	-0.185***	-0.189***
	(-5.511)	(-5.658)
TE	-0.394**	-0.425**
	(-1.985)	(-2.027)
12B_1	0.630***	0.673***
	(2.710)	(2.801)
LOG(TNA)	-0.005***	-0.005***
	(-16.257)	(-16.214)
LOG(AGE)	-0.020***	-0.020***
	(-35.383)	(-35.264)
PH	0.504***	0.171***
	(14.048)	(13.633)
PM	0.312***	0.175***
	(17.975)	(18.520)
PL	0.101***	-0.003
	(2.991)	(-0.352)
Adj. R^2	0.021	0.022

Table 5: The Effects of Mutual Fund Volatility and Fees on the Flow-Performance Relationship

The table examines the effects of different levels of volatilities and different fee charges on the flow-performance relationship. Each month, fractional performance ranks are assigned to their standard deviation of raw returns during the past 12 months. The factional rank for funds in the High Volatility rank is the top one-thirds volatile funds. Funds in the Middle Volatility rank are the medium one-third funds. And the bottom one-third funds with least volatility fall in the Low Volatility rank. Interaction terms, which include volatility ranks with performance and various fee charges with performance, will be added to into new regression (refer to Equation 3.6). T-statistics (in parentheses) calculated with Newey-West robust standard errors are reported. *, ** and *** denote significance at 10%, 5% and 1% levels, respectively.

Variable	A Excess Return	B Raw Return
C	0.071***	0.068***
	(19.916)	(18.840)
V	-0.014	0.029
	(-0.333)	(0.704)
FL	0.042***	0.055***
	(2.540)	(3.310)
BL	-0.192***	-0.173***
	(-5.631)	(-5.306)
TE	-0.411**	-0.413**
	(-2.188)	(-2.010)
12B_1	0.687***	0.577***
	(3.033)	(2.461)
LOG(TNA)	-0.005***	-0.005***
	(-16.364)	(-16.167)
LOG(AGE)	-0.020***	-0.020***
	(-35.469)	(-35.450)
PH	0.874***	0.157***
	(11.094)	(3.4891)
PM	0.440***	0.127***
	(8.560)	(2.783)
PL	0.466***	-0.005
	(4.303)	(-0.088)
V*P* VH	-2.198***	-0.671*
	(-4.976)	(-1.649)
V*P*VM	-1.388	1.292
	(-1.182)	(1.251)
V*P*VL	-1.526***	0.144
	(-2.573)	(0.195)
O*P	-0.891	0.765
	(-0.910)	(1.226)
B*P	12.335**	10.521***
	(2.499)	(4.916)
FL*P	-1.952***	-1.155***
	(-3.157)	(-3.797)
BL*P	-3.073***	-2.042***
	(-2.932)	(-4.894)
Adj. R^2	0.021	0.023

Table 6: Effects of Mutual Fund Volatility and Fees on the Flow-Performance Relationship

The table examines the effects of different levels of volatilities and different fee charges on the flow-performance relationship. Each month, fractional performance ranks are assigned to their standard deviation of raw returns during the past 12 months. The factional rank for funds in the High Volatility rank is the top one-fifth volatile funds. Funds in the Middle Volatility rank are the medium three-fifth funds. And the bottom one-fifth funds with least volatility fall in the Low Volatility rank. Interaction terms, which include volatility ranks with performance and various fee charges with performance, will be added to into new regression (refer to Equation 3.6). t-statistics (in parentheses) calculated with Newey-West robust standard errors are reported. *, ** and *** denote significance at 10%, 5% and 1% levels, respectively.

Variables	A Excess Return	B Raw Return
C	0.071***	0.068***
	(19.915)	(18.727)
V	-0.014	0.030
	(-0.321)	(0.714)
FL	0.042***	0.055***
	(2.538)	(3.309)
BL	-0.192***	-0.174***
	(-5.628)	(-5.307)
TE	-0.412**	-0.415**
	(-2.192)	(-2.011)
12B_1	0.687***	0.579**
	(3.036)	(2.465)
LOG(TNA)	-0.005***	-0.005***
	(-16.363)	(-16.159)
LOG(AGE)	-0.020***	-0.020***
	(-35.466)	(-35.426)
PH	0.878***	0.175***
	(11.427)	(4.551)
PM	0.451***	0.149***
	(9.764)	(4.059)
PL	0.472***	0.015***
	(4.546)	(0.263)
V*P* VH	-2.206***	-0.905***
	(-5.168)	(-2.645)
V*P*VM	-0.083	4.955***
	(-0.041)	(3.054)
V*P*VL	-1.816***	-0.226
	(-3.483)	(-0.399)
O*P	-0.931	0.747
	(-0.954)	(1.195)
B*P	12.424**	10.597***
	(2.515)	(4.967)
FL*P	-1.961***	-1.145***
	(-3.178)	(-3.762)
BL*P	-3.063***	-2.030***
	(-2.928)	(-4.870)
Adj. R^2	0.022	0.023

Table 7: Effects of Front-End Load and 12b_1 expense on the Flow-Performance Relationship among Funds with Different Fee Structures

Excess Return	Whole Sample	Load & 12b_1	Non-Load	Non-12b_1
C	0.071***	0.071***	0.082***	0.062***
	(19.916)	(19.909)	(21.836)	(16.820)
V	-0.014	-0.014	-0.029	-0.077***
	(-0.333)	(-0.332)	(-0.647)	(-2.727)
FL	0.042***	0.042***		-0.037
	(2.540)	(2.538)		(-1.251)
BL	-0.192***	-0.192***		-0.145
	(-5.631)	(-5.633)		(-0.541)
TE	-0.411**	-0.412**	-0.898***	-0.107
	(-2.188)	(-2.188)	(-5.836)	(-1.252)
12B_1	0.687***	0.687***	1.231***	
	(3.033)	(3.034)	(5.648)	
LOG(TNA)	-0.005***	-0.005***	-0.006***	-0.005***
	(-16.364)	(-16.362)	(-14.805)	(-10.550)
LOG(AGE)	-0.020***	-0.020***	-0.022***	-0.013***
	(-35.469)	(-35.467)	(-31.730)	(-16.135)
PH	0.874***	0.874***	0.887***	1.033***
	(11.094)	(11.094)	(9.380)	(8.182)
PM	0.440***	0.440***	0.368***	0.430***
	(8.560)	(8.559)	(5.405)	(6.499)
PL	0.466***	0.466***	0.406***	0.480**
	(4.303)	(4.303)	(2.816)	(2.163)
V*P* VH	-2.198***	-2.198***	-1.992***	-2.156***
	(-4.976)	(-4.976)	(-3.982)	(-3.060)
V*P*VM	-1.388	-1.386	-0.153	-2.482
	(-1.182)	(-1.181)	(-0.113)	(-1.529)
V*P*VL	-1.526***	-1.526***	-0.899	-2.394***
	(-2.573)	(-2.573)	(-1.334)	(-3.095)
O*P	-0.891	-0.892	-0.019	-0.647
	(-0.910)	(-0.910)	(-0.006)	(-1.018)
B*P	12.335**	12.337**	17.668***	
	(2.499)	(2.499)	(3.163)	
FL*P	-1.952***	-1.950***		0.167
	(-3.157)	(-3.155)		(0.140)
BL*P	-3.073***	-3.072***		-12.821
	(-2.932)	(-2.931)		(-1.357)
Adj. R^2	0.021	0.022	0.024	0.031

Table 8: Effects of Front-End Load and Back-End Load on the Flow-Performance Relationship among Funds with Different Performance Ranks

Excess Return	A Whole Sample	B PH	C PM	D PL
C	0.071***	0.077***	0.075***	-0.028***
	(19.916)	(12.136)	(21.193)	(-0.926)
V	-0.014	0.055	-0.081***	1.256**
	(-0.333)	(1.354)	(-4.226)	(2.369)
FL	0.042***	0.106**	0.033	0.088
	(2.540)	(2.317)	(1.911)	(0.844)
BL	-0.192***	-0.314***	-0.181***	-0.128
	(-5.631)	(-4.796)	(-4.914)	(-0.988)
TE	-0.411**	-0.066	-0.523***	-0.042
	(-2.188)	(-0.353)	(-2.536)	(-0.150)
12B_1	0.687***	-0.814**	1.043***	-0.483
	(3.033)	(-2.360)	(4.207)	(-0.708)
LOG(TNA)	-0.005***	-0.004***	-0.005***	-0.006***
	(-16.364)	(-4.548)	(-15.664)	(-4.925)
LOG(AGE)	-0.020***	-0.026***	-0.020***	-0.010***
	(-35.469)	(-14.210)	(-34.024)	(-5.073)
PH	0.874***	0.608***		
	(11.094)	(7.275)		
PM	0.440***		0.189***	
	(8.560)		(4.731)	
PL	0.466***			-0.303
	(4.303)			(-1.615)
V*P* VH	-2.198***	0.519	-0.500	4.703**
	(-4.976)	(0.770)	(-1.226)	(2.196)
V*P*VM	-1.388	6.089***	3.077***	11.674***
	(-1.182)	(2.278)	(2.823)	(4.054)
V*P*VL	-1.526***	1.126	1.035**	10.971**
	(-2.573)	(1.436)	(2.106)	(2.471)
O*P	-0.891	0.542	-0.092	-4.476*
	(-0.910)	(0.500)	(-0.084)	(-1.796)
B*P	12.335**	8.385	22.790***	-19.532
	(2.499)	(0.561)	(4.520)	(-0.729)
FL*P	-1.952***	-1.527	-1.070**	1.779
	(-3.157)	(-0.643)	(-1.936)	(0.647)
BL*P	-3.073***	-1.818	-3.443***	-1.836
	(-2.932)	(-0.449)	(-3.149)	(-0.382)
Adj. R^2	0.021	0.022	0.037	0.024

Figure 1: Mutual Fund Flow-Performance Sensitivity

This figure shows the average growth of mutual fund in response to excess return for three performance ranks. Growth is defined as a percentage change in mutual fund total net assets. Fund ranks are constructed by using Sirri and Tufano (1998) (0.2, 0.8, 0.2) approach and (0.33, 0.34, 0.33) approach.

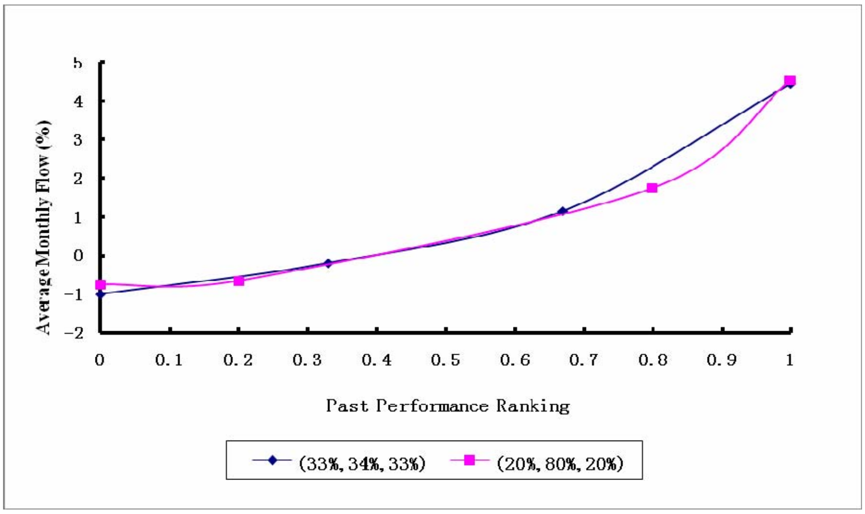

Figure 2: Mutual Fund Flow-Performance Sensitivity

This figure shows the average growth of mutual fund in response to raw return for three performance ranks. Growth is defined as a percentage change in mutual fund total net assets. Fund ranks are constructed by using Sirri and Tufano (1998) (0.2, 0.8, 0.2) approach and (0.33, 0.34, 0.33) approach.

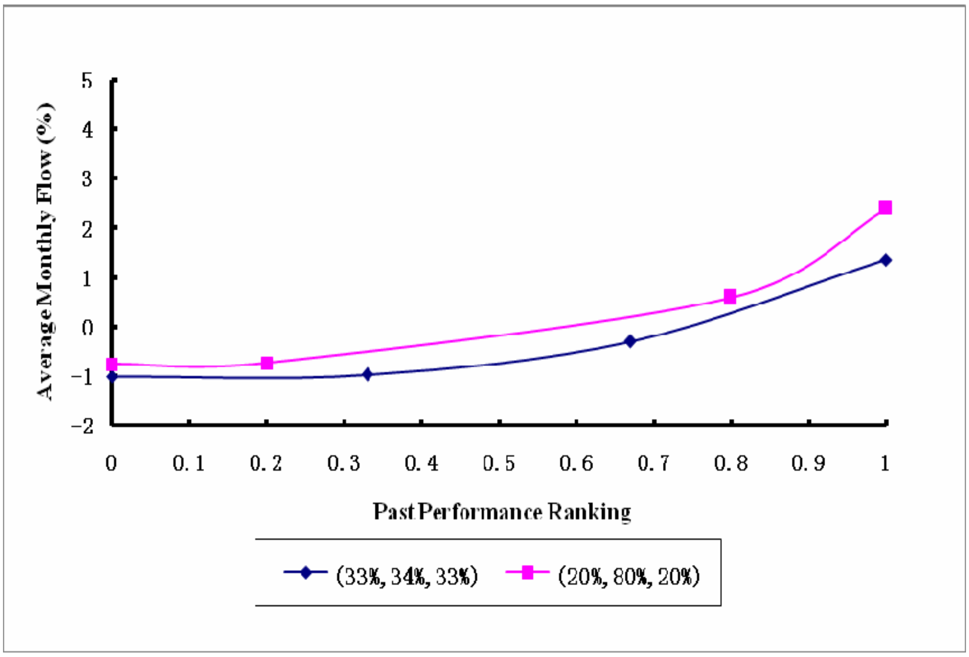

Figure 3: Effects of Different Volatility Ranks on the Flow-Performance

Relationship

It shows the change in flow-performance relation resulted from different volatilities. The red line represents the relation for funds with the highest one-third volatile performance. The blue line represents the relation for funds with middle one-third volatility. The green line represents the relation for funds with the lowest one-third volatility.

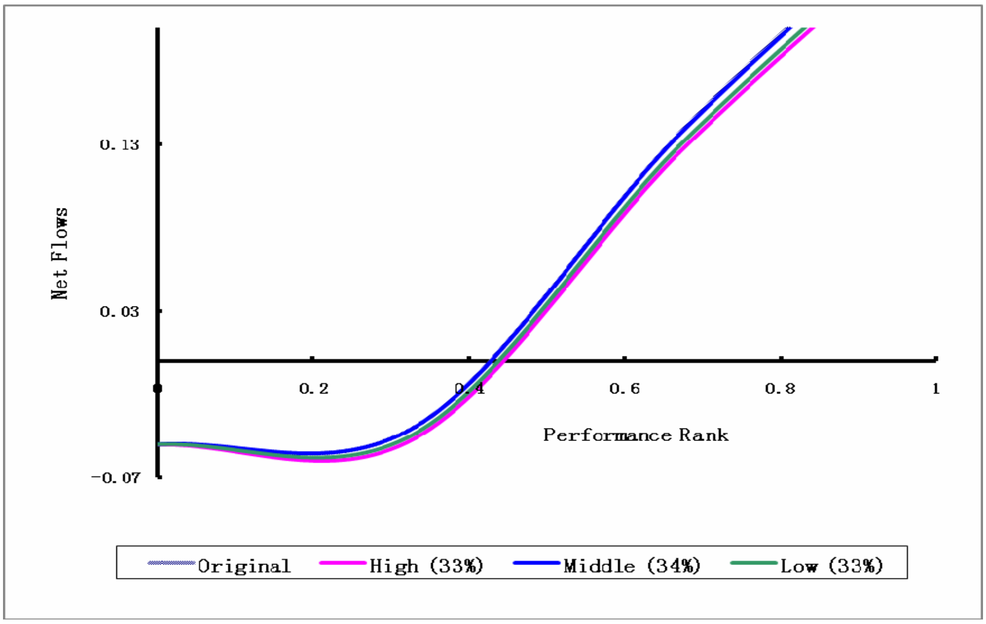

Figure 4: Effects of Different Volatility Ranks on the Flow-Performance Relationship

It shows the change in flow-performance relation resulted from different volatilities. The red line represents the relation for funds with the highest one-fifth volatile performance. The blue line represents the relation for funds with middle three-fifth volatility. The green line represents the relation for funds with the lowest one-fifth volatility.