

Market Timing and Selectivity in Feedback Trading:

Retail vs. Institutional Funds

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Abstract

This study compares the differences in equity fund investment between retail and institutional investors by developing a new empirical feedback model. First, we find that retail investors engage in positive feedback trading for market timing and selectivity. Second, positive feedback trading for market timing of retail investors is due to sell-side trades. Positive feedback trading for selectivity is generated by a combined effect of both sell- and buy-side trades. Third, there is limited evidence of overconfidence in equity mutual funds. Fourth, we fail to find any indirect evidence of disposition effect from both investors. Finally, attribution bias affects positive feedback trading of retail investors, and they apply feedback trading for market timing and selectivity according to market conditions.

JEL classification: G02, G10, G11

Keywords: Feedback trading, Market timing, Selectivity, Retail investors, Institutional investors

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1. Introduction

There is no doubt that some investors attempt to discover trends in past performances and incorporate them into their investment decisions. They are usually called feedback traders, and their trading behavior is often referred to as feedback trading. The behavioral finance literature also provides a fair number of theoretical models of feedback trading, and empirical findings support the existence of positive or negative feedback traders.¹

Trading behavior may depend upon types of investors. There are two basic types of equity fund investors: retail and institutional. Retail investors, often referred to as individual investors, buy and sell securities for personal accounts. Institutional investors trade for a group or institution. Gervais and Odean (2001) and Chuang and Susmel (2011) argue that less experienced traders, represented by individual investors, are more likely to be overconfident than experienced traders. However, Griffin and Tversky (1992) argue that professional investors may be even more overconfident when predictability is very low. Meanwhile, previous research implies that investor behavior is endogenous to market conditions, i.e., bull and bear (Chuang and Susmel, 2011; Edmans, Goldstein, and Jiang, 2015; Gervais and Odean, 2001; Kim and Nofsinger, 2007; Odean, 1999).

The above-mentioned literature suggests that psychological biases affect investors, causing them to make non-optimal decisions, and that trading activities are dependent on types of investors and market conditions. To sum, previous studies suggest that feedback trading exists in fund markets but leave the following four issues to be studied further. First, earlier studies fail to explicitly incorporate the different trading behavior of retail and institutional investors in fund markets. A large and growing segment of the mutual fund market is targeted toward institutional clients. Institutional funds have particular distribution

¹ DeLong, Shleifer, Summers, and Waldmann (1990) find that positive feedback traders are extremely irrational and are badly exploited by rational frontrunners. Barberis, Shleifer, and Vishnya (1998) discuss how a “conservatism bias” might lead investors to under-react to information, giving rise to momentum profits, and suggest that investors tend to underweight new information when they update their priors. Daniel, Hirshleifer, and Subrahmanyam (1998) propose a theory of securities market under-reactions and over-reactions that implies that investors over-react to private information signals and under-react to public information signals. Positive feedback trading also plays a central role in the model of Hong and Stein (1999). They examine a setting where under-reactions and over-reactions arise from the interaction of momentum traders and news watchers, and momentum traders make partial use of the information contained in recent price trends and ignore fundamental news.

channels, a lower fee structure, and a large initial investment when compared with retail funds. They compete with other institutional money managers including limited partnerships, hedge funds, and direct money managers.² Even though the institutional segment of the fund market has grown dramatically in recent years, few studies explore the empirical determinants of institutional trading behavior in terms of behavioral finance.

Second, Fama (1972) and Lee and Rahman (1990) partition the skill of portfolio managers into two distinct components: market timing (macro-forecasting) and selectivity (micro-forecasting). In feedback trading for market timing, fund investors chase their macro-forecasting ability of price movement in the stock market. In feedback trading for selectivity, fund investors chase their micro-forecasting ability to select the best fund style and a good-performing fund. Previous studies have seldom investigated these issues for both retail and institutional investors.

Third, most mutual fund studies have not considered the difference in behavioral characteristics between sell- and buy-side investment decisions. The possibility of an asymmetric response to return has not been explored, mainly because these studies have relied on the analysis of net flows for their investigation. Specifically, overconfidence and the disposition effect cannot be easily explained without an inflow and outflow analysis.

Finally, the concept of feedback trading is related to over-reaction and under-reaction theories that highlight overconfidence, self-attribution, and the prediction of sequential information arrival.³ The presence of a positive relationship between fund returns and subsequent cash flows provides evidence in favor of not only positive feedback but also overconfidence, because the cash flows of mutual funds may be interpreted as an investment decision and trading volume. Many studies suggest that the motivation of positive feedback trading is based on conservatism, representativeness, and the law of small numbers, but

² Del Guercio and Tkac (2002), James and Karceski (2006), and Salganik (2015) find obvious contrasts between retail and institutional funds in terms of the flow-performance relation.

³ Positive feedback is consistent with both investors' under-reaction to new information and their over-reaction to past information with a delay related to attribution biases. Barberis, Shleifer, and Vishnya (1998) and Hong and Stein (1999) show that positive feedback is due to initial under-reaction followed by correction. In DeLong, Shleifer, Summers, and Waldmann (1990) and Daniel, Hirshleifer, and Subrahmanyam (1998), it is due to an initial over-reaction followed by additional over-reaction. Daniel, Hirshleifer, and Subrahmanyam (1998) build their model around overconfidence, especially overconfidence about the validity of what investors treat as private information. Overconfidence theory implies that investors will over-react to private information signals and under-react to public information signals. Daniel, Hirshleifer, and Subrahmanyam (1998) assume that public information alters an investor's confidence in his/her original private information asymmetrically, a phenomenon known as self-attribution bias. According to Nofsinger and Sias (1999) and Kim and Nofsinger (2007), overconfident investors under-react to more relevant information in the short term and an outcome of this under-reaction leads to positive feedback trading.

biased self-attribution may play an important role in overconfidence (see Table A1 of Appendix A).⁴ However, a comprehensive study has not been executed to explain the various psychological aspects of fund investors to account for their trading behavior.

To address these issues empirically, this study compares the different investment decisions of retail and institutional investors by developing a conceptually plausible and operationally flexible empirical model, which decomposes feedback trading into market timing and selectivity. To obtain further insights, we investigate the inflows and outflows of individual funds to obtain new evidence on overconfidence and disposition effect. Our empirical model identifies whether trading behavior is caused by self-enhancing or self-protective bias due to success or failure of fund investment, respectively. This paper also explores feedback trading behavior in different market conditions.

This study contributes to the literature in three ways. First, this paper is, to our knowledge, the most comprehensive study in terms of trading behavior of different investor types (retail and institutional). Second, this paper decomposes feedback trading for market timing and selectivity by using net flows, inflows, and outflows, which are provided by the SEC's Electronic Data Gathering, Analysis, and Retrieval (EDGAR) system. They help to interpret asymmetric feedback trading, the disposition effect, and overconfidence. Last, we identify fund investors' beliefs caused by attribution bias. This identification is expected to enhance our understanding of investors' trading behavior in terms of behavioral finance.

The rest of this paper is organized as follows: Section 2 describes the data sources and descriptive statistics of sample funds. In section 3, we introduce our empirical model. Section 4 presents empirical evidence for feedback trading. Section 5 reports empirical results for the relationship between feedback trading and market conditions. The final section concludes the paper.

2. Data and Sample Funds

2.1 Retail vs. institutional funds

Mutual fund families offer retail and institutional funds to attract various types of fund investors. Retail funds target retail investors, and institutional funds serve institutional investors such as pension funds, corporations, financial institutions, foundations, state and

⁴ We summarize previous studies about investor's trading behavior in Appendix A.

local governments, and high-net-worth individuals.⁵ Fund families may offer not only exclusive funds for retail or institutional investors but also retail or institutional class shares that are just included in an ordinary fund.⁶

Even when retail and institutional funds are affiliated with the same fund family or a fund manager, institutional funds have characteristics that have not been found in retail funds. First, institutional funds have either very low or no load. Given the structure of distribution fees, institutional funds are designed to be sold in distribution channels that do not involve the provision of third party advice, or for which the fund provides little or no service to the investor. Institutional funds usually have lower operating costs and no 12b-1 fees. James and Karceski (2006) find that, despite significantly lower expenses, institutional funds, on average, do not outperform retail funds. Second, institutional funds typically have minimum investment levels of \$100,000, or even higher.⁷ Last but not least, Baker, Haslem, and Smith (2009) claim that institutional funds tend to trade securities less frequently than retail funds, and less frequent trading leads to greater tax efficiency because institutional funds hold their positions longer, which is more apt to result in long-term gains taxed at a lower rate than short-term capital gains.

Despite the dramatic growth of institutional funds, they have not been investigated enough to differentiate their characteristics from those of retail funds. Del Guercio and Tkac (2002) document empirical differences in the flow-performance relation across the mutual fund and pension fund industry segments. James and Karceski (2006) fail to find any significant relationship between fund flows and past relative performance in the institutional segment of the market. Salganik (2015) find that clients of institutional funds use more quantitatively sophisticated criteria, and provide evidence that the previously-documented convex form of the flow-performance relationship is driven mostly by retail funds. On the other hand, Baker, Haslem, and Smith (2009) and Evans and Fahlenbrach (2012) could not suggest evidence of the better performance of institutional funds relative to retail funds. In summary, these studies place more emphasis on a difference of the flow-performance

⁵ Institutional funds refer to funds that aim to manage money for large institutional investors, such as pension or endowment funds. These funds indicate in their prospectuses or names that they are institutional and typically solicit institutional investors.

⁶ The different share classes of a fund own proportional amounts of the same portfolio. A fund may have five or more share classes targeting various types of investors.

⁷ Morningstar defines institutional funds as funds with a minimum initial investment of \$100,000 or more, or funds that designate themselves as institutional funds. Given the large initial investment required (often greater than \$500,000 and frequently over \$1 million), institutional mutual funds compete with other institutional money managers including limited partnerships, hedge funds, and direct money managers.

relationship between retail and institutional funds, but cannot explain any differences in buying and redemption behavior between retail and institutional investors.

2.2 Sample funds and descriptive statistics

We use equity fund data obtained from the CRSP mutual fund database and the SEC's EDGAR system.⁸ Monthly returns, total net assets (TNAs), styles, and fund family are obtained from the CRSP data. Cash inflows and outflows are obtained from the Form N-SAR filings in the EDGAR system. We obtain a total of 6,885 domestic equity funds (18,856 class funds) of the following three styles: growth, growth and income, and mid- and small-cap.⁹ When we exclude exchange-traded funds (ETFs) and index funds, we obtain a total of 6,381 domestic equity funds (17,590 class funds). The sample period runs from January 1995 to December 2013.

Retail funds primarily serve individual investors, while institutional funds aim to manage money for large institutional investors. Some exclusive funds specialize in either retail or institutional funds. On the other hands, others have multi-class funds that serve both retail investors and institutions. In the latter case, we divide the funds into two parts: retail and institutional share classes. Retail funds include exclusive retail funds and retail share classes, and institutional funds include exclusive institutional funds and institutional share classes. We obtain 4,079 retail funds and 3,192 institutional funds. We use the data of funds when their TNAs reach one million dollars. Finally, we select 1,953 sample funds that have survived more than five years to estimate VAR models.

Among the sample funds, there are 1,659 retail funds and 1,196 institutional funds. A total of 902 funds offer both types of retail and institutional share classes. For these share classes, inflows and outflows according to investor types are not available from the EDGAR system because it provides only aggregate inflows and outflows for an individual fund, not for each share class.

⁸ Since 1994, a regulation under the Investment Company Act of 1940 has required Registered Investment Companies to file semi-annual reports (Form N-SAR A/B) with the SEC, allowing our sample period to run from January 1994 to December 2013. This study analyzes actively managed U.S. domestic equity mutual funds. Following Edelen, Evans, and Kadlec (2012), a fund is defined at the portfolio level to include all share classes. We compute TNAs and TNA-weighted average returns of fund portfolios from various fund data in the share-class level. We also manually match the CRSP fund data with EDGAR data according to fund names and fund families, because CRSP fund codes are not directly related to the central index key (CIK) in N-SAR.

⁹ According to the Strategic Insights classification from 1994 to 1998, AGG and GRO are selected for growth funds; GRI and ING for growth and income funds; and GMC and SCG for mid- and small-cap funds. On the basis of the Lipper classification from 1998 to 2013, CA and G are selected for growth funds; GI for growth and income funds; and MC, SG, and MR for mid- and small-cap funds.

The number of exclusive funds for retail and institutional investors are 757 and 294, respectively. Only for these exclusive funds, the CRSP fund data could be manually merged with the EDGAR data to obtain their inflows and outflows. We obtain inflows and outflows of 613 exclusive retail funds and 221 exclusive institutional funds. Among the matched exclusive funds, 478 retail and 174 institutional funds survived more than five years.

Figure 1 depicts the TNAs of equity funds and cumulative CRSP returns of the U.S. stock market. At the end of 2013, the TNAs of domestic equity funds in the U.S. were six trillion dollars, and our sample funds account for 61 percent of them. There has been noticeable growth of institutional funds. The TNAs of institutional funds, which account for 8% of the sample funds in 1995, increased to 35% in 2013. The rapid development of pension systems during the sample period is believed to have stimulated the growth of the institutional fund market.

<Insert Figure 1 here.>

In this study, we calculate net flows of a fund like Huang, Sialm, and Zhang (2011) as follows:

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

where $cf_{i,t}$ is the net flows of the i^{th} fund in month t using the CRSP data, $TNA_{i,t}$ is the TNAs of the i^{th} fund at the end of month t , and $r_{i,t}$ is the return of the i^{th} fund in month t . Alternatively, we also obtain inflows, outflows, and net flows of a fund from the EDGAR system.

$$\text{Inflow: } Inflow_{i,t}^{edgar} = \frac{In_{i,t}^{edgar}}{TNA_{i,t-1}(1+r_{i,t})}, \quad (2-1)$$

$$\text{Outflow: } Outflow_{i,t}^{edgar} = \frac{Out_{i,t}^{edgar}}{TNA_{i,t-1}(1+r_{i,t})}, \quad (2-2)$$

$$\text{Net flow: } Netflow_{i,t}^{edgar} = \frac{Net_{i,t}^{edgar}}{TNA_{i,t-1}(1+r_{i,t})}, \quad (2-3)$$

where $In_{i,t}^{edgar}$ is the new sales of the i^{th} fund in month t , $Out_{i,t}^{edgar}$ is the redeemed cash of the i^{th} fund in month t , $Net_{i,t}^{edgar} (\equiv In_{i,t}^{edgar} - Out_{i,t}^{edgar})$ is net sales of the i^{th} fund in month t , and $TNA_{i,t}$ is the TNAs of the i^{th} fund at the end of month t .

Table 1 presents the descriptive statistics of the 1,953 sample funds. The Panel A of retail funds indicates the average excess return of -0.0002 and the average net flows of

0.0109. The excess return, net flows, size, and age of retail share classes are higher than those of exclusive retail funds. In Panel B, institutional funds have similar figures for share classes and exclusive funds, except that most exclusive institutional funds have no front-end sales loads.

The excess return of institutional funds is slightly larger than that of retail funds because of the lower load and expense ratio of institutional funds. Institutional funds are younger and smaller than retail funds. The lower load and expense ratio are remarkable characteristics of institutional funds, which is similar to the findings of James and Karceski (2006), Evans and Fahlenbrach (2012), Salganik (2015), and Investment Company Institute (2013). These characteristics are more apparent in exclusive institutional funds than in institutional share classes.

<Insert Table 1 here.>

3. An Empirical Feedback Trading Model

3.1 Decomposing feedback trading

Feedback trading refers to trading activities whereby investors extrapolate from historical price sequences. From a theoretical perspective, its roots can be traced to both rational (informational and professional) and behavioral reasons (availability bias, conservatism, and representativeness heuristic). Empirical research has indicated the presence of significant feedback trading in equity fund markets, across different time periods, and for different investor types.

The performance of fund investors can be attributed to both market timing and selectivity. Market timing is an investment strategy to buy or sell equity funds by predicting future fund price movements, while selectivity is a selecting ability of equity funds (i.e., choosing a good-performing fund among all equity funds). In this study, feedback trading is decomposed into market timing and selectivity. Based on this concept, fund return consists of the following three parts:

$$r_{i,t} = \frac{(r_{i,t} - r_{m,t})}{(a)} + \frac{(r_{m,t} - E_{t-1}(r_{m,t}))}{(b)} + \frac{E_{t-1}(r_{m,t})}{(c)}, \quad (3)$$

where $r_{i,t}$ is the return of the i^{th} fund in month t , $r_{m,t}$ is the CRSP market return in month t ,

and $E_{t-1}(r_{m,t})$ is the expected market return at the end of month t-1.¹⁰ In Equation (3), (a) is the i^{th} fund's excess return over the market return, (b) is the unexpected market return, and (c) is the expected market return at the end of month t-1. The first term (a) is related to selectivity because the i^{th} fund's excess return over the market originates from selecting a good-performing fund. The second term (b) is closely related to market timing because unexpected market return is a source of profit from asset allocation. If fund investors are successfully able to chase this return, they must engage in feedback trading for market timing.

Selection of a fund consists of two parts: selecting a fund style and selecting a fund among a given fund style group. Hence, selectivity is further divided into style selectivity and fund selectivity. We can decompose selectivity (a) into style selectivity and fund selectivity as follows:

$$\frac{r_{i,t} - r_{m,t}}{(a)} = \frac{(r_{i,t} - r_{s,t})}{(d)} + \frac{(r_{s,t} - r_{m,t})}{(e)}, \quad (4)$$

where $r_{i,t}$ is the return of the i^{th} fund in month t, $r_{m,t}$ is the CRSP market return in month t, $r_{s,t}$ is the return of the s^{th} fund style group in month t, and S means the growth funds, growth and income funds, or mid- and small-cap funds.

On the right-hand side of Equation (4), the first term (d) is a fund excess return over the return of a style group and the second term (e) is a style excess return over the market return. If investors chase a fund excess return over the style group (d), such a strategy is related to fund selectivity. Meanwhile, if investors chase the style excess return over the market (e), they attempt to select a style group to beat the market. This strategy can be called feedback trading for style selectivity.

This concept of a fund's return decomposition is directly applied to fund cash flows as follows:

$$cf_{i,t}^G = \frac{(cf_{i,t}^G - cf_{m,t}^G)}{(a')} + \frac{(cf_{m,t}^G - E_{t-1}(cf_{m,t}^G))}{(b')} + \frac{E_{t-1}(cf_{m,t}^G)}{(c')}, \quad (5)$$

$$\frac{cf_{i,t}^G - cf_{m,t}^G}{(a')} = \frac{(cf_{i,t}^G - cf_{s,t}^G)}{(d')} + \frac{(cf_{s,t}^G - cf_{m,t}^G)}{(e')}, \quad (6)$$

¹⁰ On the other hand, alternative ways of calculating return decompositions are possible by replacing expected market return by the risk-free rate or zero return. See the following decompositions: $r_{i,t} = (r_{i,t} - r_{m,t}) + (r_{m,t} - r_{f,t}) + r_{f,t}$ or $(r_{i,t} - r_{m,t}) + r_{m,t}$. Here, $r_{f,t}$ is a risk-free rate in month t. For these two alternative decompositions, we obtain very similar results to those found in this study.

where $cf_{i,t}^G$ represents cash flows of the i^{th} fund included in an investor group G in month t , $cf_{m,t}^G$ represents cash flows included in an investor group G in month t , $E_{t-1}(cf_{m,t}^G)$ represents expected cash flows included in an investor group G at the end of the month $t-1$, $cf_{s,t}^G$ represents cash flows of the s^{th} style group of funds included in an investor group G in month t , and G means the retail or institutional investors' group.

The relationship between (b) in Equation (3) and (b') in Equation (5) indicates feedback trading for market timing. Applying the same concept, the relationship between (a) and (a') means feedback trading for selectivity. Specifically, the relationship between (d) and (d') is defined by feedback trading for fund selectivity, and the relationship between (e) and (e') is defined by feedback trading for style selectivity. In Equations (3) and (5), $E_{t-1}(r_{m,t})$ and $E_{t-1}(cf_{m,t}^G)$ cannot be determined easily by any model. In the absence of perfectly reliable information for the expected market return and cash flows, they can be replaced by $r_{m,t-1}$ and $cf_{m,t-1}^G$, respectively.¹¹

Table 2 shows summary statistics of average fund returns and net flows. Because retail and institutional investors have different sample funds, they have different returns and cash flows. Unexpected market returns in Panel A are positive for both retail and institutional investors, while funds' excess returns over the market in Panel B are negative and positive for retail and institutional investors, respectively. It is noteworthy that all contemporaneous correlations between returns and corresponding cash flows are significantly positive, which implies that fund investment is likely to depend on the fund performance and stock market trend. Interestingly, the correlations for retail investors are larger than those for institutional investors. It can be interpreted that retail investors are more sensitive to fund returns than institutional investors.

<Insert Table 2 here.>

3.2 Vector autoregressive (VAR) models

To understand the dynamic relationships between fund performance and trading activities of investors, we investigate the feedback trading of fund investors using the following bivariate vector auto-regressive (BVAR) model.

¹¹ We also employ the Warther's (1995) model to estimate expected market returns and cash flows; however, the results do not change qualitatively.

$$\text{BVAR: } \begin{bmatrix} cf_{fb,t}^G \\ r_{fb,t} \end{bmatrix} = \begin{bmatrix} \alpha_{cf}^G \\ \alpha_r \end{bmatrix} + \sum_{k=1}^K \beta_k \begin{bmatrix} cf_{fb,t-k}^G \\ r_{fb,t-k} \end{bmatrix} + \begin{bmatrix} e_{cf,t}^G \\ e_{r,t} \end{bmatrix}, \quad (7)$$

where fb represents feedback trading, $cf_{fb,t}^G$ represents feedback cash flows of the investor group G in month t, $r_{fb,t}$ represents the corresponding feedback return in month t, G is the retail or institutional fund group, and K is the lag order determined by Schwarz Bayesian criterion,

$$cf_{fb,t}^G = \begin{cases} (a') dcf_{i,m,t}^G = cf_{i,t}^G - cf_{m,t}^G \\ (b') dcf_{m,t}^G = cf_{m,t}^G - E_{t-1}(cf_{m,t}^G) \\ (d') dcf_{i,s,t}^G = cf_{i,t}^G - cf_{s,t}^G \\ (e') dcf_{s,m,t}^G = cf_{s,t}^G - cf_{m,t}^G \end{cases}, \text{ and } r_{fb,t} = \begin{cases} (a) dr_{i,m,t} = r_{i,t} - r_{m,t} \\ (b) dr_{m,t} = r_{m,t} - E_{t-1}(r_{m,t}) \\ (d) dr_{i,s,t} = r_{i,t} - r_{s,t} \\ (e) dr_{s,m,t} = r_{s,t} - r_{m,t} \end{cases}.$$

In Equation (7), BVAR models for $(dcf_{i,m,t}^G$ and $dr_{i,m,t})$ and $(dcf_{m,t}^G$ and $dr_{m,t})$ test feedback trading for selectivity and market timing, respectively. Likewise, BVAR models for $(dcf_{i,s,t}^G$ and $dr_{i,s,t})$ and $(dcf_{s,m,t}^G$ and $dr_{s,m,t})$ test feedback trading for fund selectivity and style selectivity, respectively. Estimated coefficients of the BVAR models show the responses of investors to the past corresponding return difference for market timing and selectivity. We interpret the results using the sum of lagged coefficients in a regression equation of cash flows. This can help identify overall and possible effects of past return differences on investors' trading activities over time. In addition, we use the cumulative impulse-response functions (IRFs) to study the long-term responses of cash flows to a fund return shock.

4. Empirical Evidence of Feedback Trading Behavior

4.1 Feedback trading for market timing and selectivity

This section investigates feedback trading of fund investors for market timing and selectivity. We also compare the results between retail and institutional investors by using our decomposition model. Table 3 reports the estimation results of net flows regressions. If the sum of coefficients ($\sum \beta$) is significantly positive (negative), fund investors do positive (negative) feedback trading in response to past fund performance.¹²

In Panel A, we find that retail investors do positive feedback trading for market timing (i.e., retail investors base their investment decisions on past market performance). However, there is no evidence that institutional investors chase market returns for market

¹² Even when we use the coefficient of the first lagged return to test feedback trading, we obtain very similar results to those found in this study.

timing. The same phenomenon is observed for the estimation results of feedback trading for selectivity in Panel B. The average of $\sum \beta$ (0.2125) for retail funds is slightly significant. It indicates that retail investors do positive feedback trading for selectivity. The proportion of the number of funds that show positive (negative) feedback trading for selectivity is 23% (1%). The proportion of the total size of funds with a positive (negative) sum of coefficients is 45% (0%), which implies that retail investors of large funds are more likely to trade positively based on the corresponding return. Nevertheless, almost no institutional investors show feedback trading for selectivity.

Panel C shows the estimation results of feedback trading for style selectivity. Interestingly, all style groups of retail funds show feedback trading for style selectivity while those of institutional funds do not. The results of feedback trading for fund selectivity in Panel D presents results very similar to those in Panel B. The estimation results conclude that retail investors are likely to do positive feedback trading for market timing and selectivity, but institutional investors are not.¹³

<Insert Table 3 here.>

Why is the trading behavior of institutional investors different from that of retail investors in terms of the feedback trading? Possible answers may be found as follows: retirement plans, the level of learning bias and trading experience, and large investments of financial and general institutions.

First, we must look at institutional trading activities from the viewpoint of pension finance. In the 1990s, defined contribution plans, such as 401(k) plans, became one of the primary sources through which investors buy mutual funds. Institutional funds and share classes are most often found in employer-sponsored retirement plans. Employees in such plans behave as mutual fund investors. A pension plan may allow workers to contribute part of their current income from wages on a regular basis into an investment plan for retirement purposes. Employees buy and sell funds depending on their life plans, such as retirement, education, marriage, and so forth. They are less likely than general retail investors to depend on past performance. Many institutional funds represent aggregate investments of employees in mutual funds. Consequently, institutional funds do not necessarily show such return-chasing behavior as that of retail funds.

¹³ We do not report the estimation results of the return regression in our BVAR model. The unreported coefficients of fund flows indicate that fund flows do not predict subsequent returns at all.

Second, the previous literature reveals why institutional investment behavior differs from retail investors' behavior. The most striking difference in trading activities between retail and institutional investors is the level of learning bias and trading experience. Gervais and Odean (2001) find that biased self-attribution causes a degree of overconfidence, and less experienced traders (retail investors) will be more overconfident than more experienced traders (institutional investors). Chuang and Susmel (2011) also provide evidence that individual investors trade more actively than institutional investors. In general, individual investors as a group are regarded as less experienced and amateurish investors, while institutional investors as a group are regarded as more experienced and professional investors. Thus, we would expect that such institutional investors trade less frequently than retail investors. Institutional investors may keep careful records rather than relying on past performance to learn more quickly.

Finally, distribution channels and the initial amount of institutional funds would mitigate feedback trading. James and Karceski (2006) claim that the lack of significant flow-performance relationship among institutional funds may reflect the fact that institutional funds constitute "captured money." Fiduciaries and other institutional investors face little oversight from their clients, and simply park money in mutual funds with which they have an affiliation. Accordingly, they do not care about past performance. This may also be a kind of agency problem. Moreover, institutional funds target high-net-worth investors with low management fees. They require very high minimum investment levels of \$5 or \$10 million, or even higher. This minimum investment requirement makes institutional investors less sensitive to past performance.

Now we return to the estimation results of our BVAR models. To aggregate over coefficient estimates, we employ IRF analysis. This procedure illustrates how the endogenous variables respond to each other over time. Figure 2 shows the cumulative responses of cash flows to a market return shock with their 95% error bands. For retail funds, the cumulative responses of net flows to a market return shock are positive and permanent. This implies that a return shock has a permanently positive effect on the net flows of retail investors. On the other hand, a market return shock has no effect on net flows of institutional investors. We interpret this result as evidence that unexpected market returns have a positive effect on subsequent net flows of retail investors, but not on those of institutional investors.

<Insert Figure 2 here.>

Figure 3 indicates the responses of net flows to a style excess return shock for the three types of fund style. All panels show that the effect of the style excess return shock on net flows for style selectivity remains permanently positive for retail investors. For institutional investors, such an effect also exists but is much weaker than for retail investors. In the case of growth and income funds in Panel B, the style excess return shock has almost zero effect on net flows. These results of the impulse response functions conclude that the style excess return shock has a permanently positive effect on net flows for style selectivity in retail funds more than in institutional funds.

<Insert Figure 3 here.>

As shown in Table 1, there might be slight differences in characteristics between share classes and exclusive funds. For both retail and institutional investors, exclusive funds may have more typical characteristics than the corresponding share classes. In this respect, we again compare the trading activities of retail investors to those of institutional investors using exclusive funds only. Interestingly, Table 4 also shows positive feedback trading for market timing and selectivity for retail investors, but not for institutional investors. This finding indicates that exclusive funds for retail and institutional investors provide the same empirical results as those for the total retail and institutional funds, respectively.

<Insert Table 4 here.>

In sum, our findings indicate that past performance is an important predictor of corresponding trading activities of retail investors, but not of institutional investors.

4.2 Feedback trading, overconfidence, and the disposition effect

Fund cash flows play an important role in understanding the trading behavior of investors from the following three viewpoints in mutual fund studies. First, many studies analyze the relationship of net flows with past performance to investigate feedback trading (Edelen and Warner, 2001; Jank, 2012; Warther, 1995).¹⁴ Edmans, Goldstein, and Jiang (2015) theoretically suggest that the feedback has an asymmetric effect on trading behavior. In other words, the feedback increases (reduces) the profitability of buying (selling) on good (bad) news. This suggests that feedback trading should be tested for inflows and outflows, as well as for net flows, to consider both the purchase and redemption behavior of investors.

Second, cash flows can be considered as not only investment decisions, but also

¹⁴ Ha and Ko (2017) investigate the relationship between past performance and subsequent cash flows.

trading volume that signals overconfidence. Gervais and Odean (2001) and Statman, Thorley, and Vorkink (2006) suggest that changes in trading volume are the primary testable implication of overconfidence theory. In an aggregate stock market, trading volume is the same as buying (or selling) volume. In the case of mutual funds, however, trading volume can be defined in various ways (i.e., inflows; outflows; and total flows, i.e., the sum of inflows and outflows). While the concept of trading volume in stock markets is closest to total flows (inflows plus outflows) in mutual funds, inflows are considered as buy-side trading volume. We focus on the distinct implications associated with trading volume over time in terms of not only total flows but also inflows. To confirm the overconfidence theory, total flows and inflows must have a positive relationship with corresponding return measures. Inflows are a measure for overconfidence of buy-side trading.

Last, the disposition effect can be tested by fund outflows because it depends on the selling behavior of investors (Shefrin and Statman, 1985). Unfortunately, it is not possible to test the disposition effect without individual investors' information from personal accounts. In this study, however, we test the disposition effect indirectly by using fund outflows and corresponding past performance. When we use fund outflows, it is difficult to differentiate the disposition effect from overconfidence. If outflows respond positively to corresponding returns, we interpret this as indirect evidence of the disposition effect.

Table 5 shows the trading behavior of retail investors using total flows, net flows, inflows, and outflows. The results of net flows in Table 5 must be similar to those in Table 4 because the sample funds are exclusive retail funds matched to the EDGAR data. Panel A shows the results of feedback for market timing. We first examine why the net flows of retail investors respond to the corresponding returns. An analysis of inflows and outflows can reveal detailed interpretations of total flows and net flows. We easily find that the positive feedback of net flows for market timing is due to the negative effects of outflows but not to the insignificant effects of inflows. That is, retail investors reduce sell-side trades after an increase of the corresponding return, which results in the feedback trading of net flows for market timing.

On the other hand, the positive feedback trading of net flows for selectivity shown in Panel B is due to the combined effect of buy- and sell-side trades. Although both inflows and outflows are marginally insignificant, the positive feedback of inflows and the negative feedback of outflows result in the positive feedback of net flows for selectivity. In Panel C, the same reasoning holds for the positive feedback for style selectivity of growth funds. In the

case of style selectivity of growth and income funds (mid- and small-cap funds), the positive (negative) feedback of inflows (outflows) plays an important role in the positive feedback of net flows. We also find such mixed effects of positive feedback for fund selectivity in Panel D.

Regarding overconfidence, it is hard to say that retail investors have overconfidence when they invest in equity funds, despite weak evidence of feedback trading for selectivity in the two columns of total flows. However, the feedback of inflows for selectivity shows overconfidence for 14% (33%) of the sample in the number of funds (in the size of funds). This implies that many, not most, retail investors are overconfident in buying behavior for selectivity. Such overconfidence that is limited to buy-side trades is also found in the positive feedback trading for style and fund selectivity in Panels C and D.

On the other hand, when we see the two columns of outflows, the sums of coefficients are all negative irrespective of their statistical significance. These findings show positive feedback trading for market timing and selectivity from the viewpoint of sell-side. In the feedback of outflows for selectivity, only 3% of retail investors sell their funds when their corresponding returns are high. The empirical results of outflows suggest indirect evidence that is not consistent with the disposition effect in mutual funds.¹⁵ Chang, Solomon, and Westerfield (2016) show that the disposition effect applies only to non-delegated assets like individual stocks; delegated assets, like mutual funds, exhibit a robust reverse-disposition effect. Our indirect evidence is consistent with the conclusions of Chang, Solomon, and Westerfield (2016).

<Insert Table 5 here.>

Table 6 shows the trading behavior of institutional investors using total flows, net flows, inflows, and outflows. Unlike the results in Table 5, it is very hard to find statistically significant sums of coefficients, with a small exception for the feedback for selectivity.

Our findings conclude that the feedback trading behavior of retail investors is different from that of institutional investors when investing in equity mutual funds. Retail investors do engage in feedback trading for market timing and selectivity, but institutional investors do not. We also find limited evidence of overconfidence for retail investors, but not for institutional investors. These conclusions may originate from the fact that institutional

¹⁵ Because we do not use each retail investor's trading records, our evidence can be thought of as indirect at most.

investors are more experienced and professional than retail investors (Chuang and Susmel, 2011; Menkhoff, 2010). Institutional investors may not overestimate the degree to which they depend on past performance, and they do not trade more aggressively following past gains. On the other hand, the disposition effect is not found for both retail and institutional investors, which is consistent with a recent study by Chang, Solomon, and Westerfield (2016).

<Insert Table 6 here.>

4.3 Attribution bias: self-enhancing bias and self-protective bias

We find positive feedback trading and buy-side overconfidence of retail fund investors in Table 5. Positive feedback trading and buy-side overconfidence may arise from the attribution bias of retail fund investors. We develop a new measure to investigate a relationship between attribution bias and feedback trading following Gervais and Odean (2001). They note that investors learn about their trading ability and explain how a bias in this learning can create an overconfident trader. Attribution bias is people's tendency to attribute positive events to their own character (self-enhancing bias) and to attribute negative events to external factors (self-protective bias).¹⁶ We investigate whether attribution bias affects the trading behavior of fund investors, and consider what type of attribution bias is more likely.

According to the overconfidence theory of Gervais and Odean (2001), traders learn about their abilities through investment performance, the level of learning bias, and trading experience. These are directly related to the attribution bias of retail investors. We develop a measure in Equation (8) to analyze the effect of retail investors' attribution bias on trading behavior. The investment skill is estimated as follows.

$$Skill_t = cf_{fb,t-T:t-1} \times r_{fb,t-T:t-1}, \quad (8)$$

where $Skill_t > 0$ ($Skill_t \leq 0$) represents the investment success (failure) of retail investors. T is the past investment period (T = 1 and 3 months).

To study the effect of retail investors' attribution bias, we estimate the following regression model:

$$cf_{fb,t} = \alpha_{cf} + \sum_{k=1}^K \beta_k r_{fb,t-k} I(Skill_t > 0) + \sum_{k=1}^K \delta_k r_{fb,t-k} I(Skill_t \leq 0) + \sum_{k=1}^K \gamma_k cf_{fb,t-k} + e_{cf}, \quad (9)$$

where $I(Skill_t > 0)$ equals one if $Skill_t > 0$, and zero, otherwise, and $I(Skill_t \leq 0)$ equals

¹⁶ See Miller and Ross (1975), Taylor (1991), and Fiske and Taylor (1991).

one if $Skill_t \leq 0$, and zero, otherwise. Positive $\sum \beta$ indicates that the positive feedback trading is caused by self-enhancing bias, and positive $\sum \delta$ indicates that the positive feedback trading is caused by self-protective bias.

Table 7 presents the estimation results for retail investors using Equations (8) and (9). The sample for this analysis consists of retail funds that show positive feedback trading in Table 3. Because the number of lags is two or three in equation (9), the results for one and three months are reported. Panel A reports the results of attribution bias in the feedback trading for market timing. We find that the feedback trading for market timing is driven by both self-enhancing and self-protective biases, irrespective of the past investment period. The sum of coefficients is larger for self-enhancing bias than for self-protective bias, although Chi-square statistics reveal that both effects are statistically significant.

Panel B reports the results of attribution bias in the feedback for selectivity. The effect of self-enhancing bias plays a more important role in feedback trading than the self-protective bias. That is, the self-enhancing bias is more distinct than the self-protective bias for both one month and three months. This means that fund investors are more likely to learn about their selection ability within a relatively short period and, in this case, the self-enhancing bias would be stronger than the self-protective bias. This pattern of attribution bias also holds in Panels C and D. We conclude that investors' beliefs caused by attribution bias affect positive feedback trading and overconfidence, and the self-enhancing bias is stronger than the self-protective bias. The difference between self-enhancing and self-protective biases is more apparent in a relatively short period.

<Insert Table 7 here.>

5. Feedback Trading in Different Market Conditions

Retail investors' behavior would differ in bull and bear market conditions (Daniel, Hirshleifer, and Subrahmanyam, 1998; Gervais and Odean, 2001; Kim and Nofsinger, 2007). Edmans, Goldstein, and Jiang (2015) suggest that the feedback effect increases (reduces) the profitability of buying (selling) on good (bad) news. Recently, Starks and Sun (2016) claim that investor learning about manager ability weakens when uncertainty increases. Franzoni and Schmalz (2016) find that fund flow-performance sensitivity varies in different stages of the market cycle. Previous studies theoretically and empirically suggest that different market conditions have an asymmetric effect on trading behavior.

We test the trading behavior of retail investors in different market conditions by

estimating the following regression model.

$$cf_{fb,t} = \alpha_{cf} + \sum_{k=1}^K \beta_k r_{fb,t-k} I(bull_t) + \sum_{k=1}^K \delta_k r_{fb,t-k} I(bear_t) + \sum_{k=1}^K \gamma_k cf_{fb,t-k} + e_{cf}, \quad (10)$$

where $I(bull_t)$ equals one if month t is in an up market, and zero, otherwise, $I(bear_t)$ equals one if month t is in a down market, and zero, otherwise. If $\sum \beta > 0$ ($\sum \delta > 0$), it indicates evidence of positive feedback trading in a bull (bear) market. We classify a bull market and a bear market according to the trend of CRSP stock market return in Figure 1. The bull market periods are 1995–1998, 2003–2006, 2009, and 2012–2013, and the bear market periods are 1999–2002, 2007–2008, and 2010–2011.¹⁷

Table 8 shows the feedback trading behavior of retail investors in different market conditions. Panel A presents the results of feedback trading of retail investors for market timing. Both $\sum \beta > 0$ and $\sum \delta > 0$ are positive, and they are not much different, which implies that retail investors engage in positive feedback trading for market timing in both bull and bear markets.

Panel B presents the results of feedback trading for selectivity. In this case, market condition plays an important role in feedback trades. Although the average $\sum \beta$ is slightly larger than the average $\sum \delta$, positive feedback trading seems to be slightly weaker in a bull market than in a bear market. The proportion of the number of funds (fund size) with positive sum of coefficients is 15% (27%) in a bear market, but it is 9% (15%) in a bull market (i.e., feedback trading for selectivity is more common in a bear market). This is evidence of an asymmetric effect of market condition on feedback trading for selectivity. In Panel C, we find that this asymmetric effect is more apparent in the feedback trading for style selectivity. The sum of coefficients is significantly positive for all three style groups of funds in a bear market, but only for the style of mid- and small-cap funds in a bull market. In Panel D, the results of positive feedback trading for fund selectivity are not much different from those in Panel B.

The above findings provide an important implication for positive feedback trading of retail investors in equity fund investment. While retail investors attempt to engage in feedback trading for market timing irrespective of market conditions, they tend to engage in feedback trading for selectivity more frequently in a bear market because selectivity is not very important due to the relatively high performance of most funds in a bull market. Which selectivity, then, is more important between style and fund selectivity? Panels C and D show

¹⁷ We also define market conditions by the sign of cumulative returns during the past 6, 12, 24, and 36 months. The results are similar to those in Table 8.

that style selectivity is more important than fund selectivity in a bear market.

Why is style selectivity more meaningful in a bear market? There are two practical reasons to be considered. The first reason is the limited number of funds offered by a sales company. When retail investors buy equity funds, the sales company offers a very limited number of equity funds in the same style groups. Retail investors are not offered enough choices to satisfy their preferences. However, the offered funds would include all three style groups of equity funds. Retail investors are more likely to consider which style is fitted to their investment goal. The second is the difficulty of selecting a specific fund with high performance in the near future. Even if a retail investor is allowed to choose a promising fund among a lot of funds in the same style group, fund selection is an extremely difficult task in his/her life. Eventually, retail investors are apt to choose a fund style according to past style performance, but not a specific fund.

In sum, our results suggest that the feedback trading of retail investors varies between bull and bear market conditions, which is consistent with the extant literature.

<Insert Table 8 here.>

6. Concluding Remarks

Many studies have investigated psychological biases that may affect investors' behavior, causing investors to make non-optimal decisions. Our study compares investment decisions between retail and institutional investors by developing an empirical feedback trading model. We believe that our findings contribute to the extant literature on the trading behavior of fund investors.

Our empirical findings are summarized as follows: First, retail investors engage in positive feedback trading for market timing and selectivity. However, there is no evidence that institutional investors chase past performance. Second, positive feedback trading of retail investors for market timing is due to sell-side trading. Positive feedback trading for selectivity is generated by a combined effect of both sell- and buy-side trades. Third, there is limited evidence of overconfidence in equity mutual funds. Fourth, we fail to find any indirect evidence of the disposition effect. Fifth, attribution bias affects positive feedback trading of retail investors, and self-enhancing bias is stronger than self-protective bias in feedback trading for selectivity. Finally, retail investors apply feedback trading for market timing and selectivity according to market conditions.

This study sheds new lights on the investment decisions of fund investors in three ways. First, this is the most comprehensive study in terms of the trading behavior of different investor types (retail and institutional). Second, this study decomposes feedback trading for market timing and selectivity using net flows, inflows, and outflows, which are provided by the SEC's EDGAR system. These cash flows help us interpret asymmetric feedback trading, the disposition effect, and overconfidence. Last, we identify fund investors' beliefs caused by attribution bias. This identification is expected to enhance our understanding of investors' trading behavior in terms of behavioral finance.

References

- Bailey, W., Kumar, A., Ng, D., 2011. Behavioral biases of mutual fund investors. *Journal of Financial Economics* 102, 1-27.
- Baker, K. H., Haslem, J. A., Smith, D. M., 2009. Performance and characteristics of actively managed institutional equity mutual funds. *Journal of Investing* 18, 27-44.
- Barberis, N., Shleifer, A., Vishnya, R., 1998. A model of investor sentiment. *Journal of Financial Economics* 49, 307-343.
- Barberis N., Thaler, R., 2003. Chapter 18 a survey of behavioral finance. *Handbook of the Economics of Finance* 1, 1053-1128.
- Barberis, N., Xiong, W., 2009. What drives the disposition effect? An analysis of a long-standing preference-based explanation. *Journal of Finance* 64, 751-784.
- Birru, J., 2015. Confusion of confusions: a test of the disposition effect and momentum. *Review of Financial Studies* 28, 1849-1873.
- Brown, D. P., Wu, Y., 2016. Mutual fund flows and cross-fund learning within families. *Journal of Finance* 71, 383-424.
- Cao, C., Chang, E. C., Wang, Y., 2008. An empirical analysis of the dynamic relationship between mutual fund flow and market return volatility. *Journal of Banking and Finance* 32, 2111-2123.
- Chang, Y., Solomon, D., Westerfield, M., 2016. Looking for someone to blame: delegation, cognitive dissonance, and the disposition effect. *Journal of Finance* 71, 267-302.
- Chevalier, J., Ellison, G., 1997. Risk taking by mutual funds as a response to incentives. *Journal of Political Economy* 105, 1167-1200.
- Chuang, W., Susmel, R., 2011. Who is the more overconfident trader? Individual vs. institutional Investors. *Journal of Banking and Finance* 35, 1626-1644.
- Daniel, K., Hirshleifer, D., Subrahmanyam, A., 1998. Investor psychology and security market under- and over-reaction. *Journal of Finance* 53, 1839-1885.
- De Bondt, W. F. M., Thaler, R. H., 1985. Does the stock market over-react? *Journal of Finance* 40, 793-805.
- De Bondt, W. F. M., Thaler, R. H., 1987. Further evidence on investor over-reaction and stock market seasonality. *Journal of Finance* 42, 557-581.
- De Long, J. B., Shleifer, A., Summers, L., Waldmann, R. J., 1990. Positive feedback investment strategies and destabilizing speculation. *Journal of Finance* 45, 379-395.
- Del Guercio, D., Tkac, P., 2002. The determinants of the flow of funds on managed portfolios:

- mutual funds versus pension funds. *Journal of Financial and Quantitative Analysis* 37, 523-557.
- Edelen, R., 1999. Investor flows and the assessed performance of open-end mutual funds. *Journal of Financial Economics* 53, 439-466.
- Edelen, R. M., Evans, R. B., Kadlec, G. B., 2012. Disclosure and agency conflict: evidence from mutual fund commission bundling. *Journal of Financial Economics* 103, 308-326.
- Edelen, R. M., Warner, J. B., 2001. Aggregate price effects of institutional trading: a study of mutual fund flow and market returns. *Journal of Financial Economics* 59, 195-220.
- Edmans, A., Goldstein, I., Jiang, W., 2015. Feedback effects, asymmetric trading, and the limits to arbitrage. *American Economic Review* 10, 376-379.
- Evans, R. B., Fahlenbrach, R., 2012. Institutional investors and mutual fund governance: evidence from retail-institutional fund twins. *Review of Financial Studies* 25, 3530-3571.
- Fant, L. F., 1999. Investment behavior of mutual fund shareholders: the evidence from aggregate fund flows. *Journal of Financial Markets* 2, 391-402.
- Fant, L. F., O'Neal, E. S., 1999. Do you need more than one manager for a given equity style? *Journal of Portfolio Management* 25, 68-75.
- Fama, E. F., 1972. Components of investment performance. *Journal of Finance* 27, 551-567.
- Fiske, S. T., Taylor, S. E., 1991. *Social Cognition* (2nd ed.). New York: McGraw-Hill.
- Franzoni, F., Schmalz, M. C., 2016. Fund flows and market states. *Unpublished working paper*. <<http://ssrn.com/abstract=2263944>>.
- Frazzini, A., 2006. The disposition effect and under-reaction to news. *Journal of Finance* 61, 2017-2046.
- Gervais, S., Odean, T., 2001. Learning to be overconfident. *Review of Financial Studies* 14, 1-27.
- Griffin, D., Tversky, A., 1992. The weighting of evidence and the determinants of overconfidence. *Cognitive Psychology* 24, 411-435.
- Guo, M., Ou-Yang, H., 2015. Feedback trading between fundamental and nonfundamental information. *Review of Financial Studies* 28, 247-296.
- Ha, Y., Ko, K., 2017. Why do fund managers increase risk? *Journal of Banking and Finance* 78, 108-116.
- Hong, H., Lim, T., Stein, J., 2000. Bad news travels slowly: size, analyst coverage, and the profitability of momentum strategies. *Journal of Finance* 55, 265-295.

- Hong, H., Stein, J., 1999. A unified theory of under-reaction, momentum trading, and over-reaction in asset markets. *Journal of Finance* 54, 2143-2184.
- Huang, J., Sialm, C., Zhang, H., 2011. Risk shifting and mutual fund performance. *Review of Financial Studies* 24, 2575-2616.
- Huang, J., Wei, K. D., Yan, H., 2007. Participation costs and the sensitivity of fund flows to past performance. *Journal of Finance* 62, 1273-1311.
- Investment Company Institute, 2013. Ownership of mutual funds, shareholder sentiment, and use of the internet. *ICI Research Perspective* 19, 1-46.
- Ippolito, R. A., 1992. Consumer reaction to measures of poor quality: evidence from the mutual fund industry. *Journal of Law and Economics* 35, 45-70.
- Ivkovic, Z., Weisbenner, S., 2009. Individual investor mutual fund flows. *Journal of Financial Economics* 92, 223-237.
- Jank, S., 2012. Mutual fund flows, expected returns, and the real economy. *Journal of Banking and Finance* 36, 3060-3070.
- James, C., Karceski, J., 2006. Investor monitoring and differences in mutual fund performance. *Journal of Banking and Finance* 30, 2787-2808.
- Kim, K. A., Nofsinger, J. R., 2007. The behavior of Japanese individual investors during bull and bear markets. *Journal of Behavioral Finance* 8, 138-153.
- Lee, C. F., Rahman, S., 1990. Market timing, selectivity, and mutual fund performance: an empirical investigation. *Journal of Business* 63, 261-278.
- Lo, A. W., Mackinlay, A. C., 1990. When are contrarian profits due to stock market over-reaction? *Review of Financial Studies* 3, 175-205.
- Lynch, A. W., Musto, D. K., 2003. How investors interpret past fund returns. *Journal of Finance* 58, 2033-2058.
- Menkhoff, L., 2010. The use of technical analysis by fund managers: international evidence. *Journal of Banking and Finance* 34, 2573-2586.
- Miller, D. T., Ross, M., 1975. Self-serving biases in the attribution of causality: fact or fiction? *Psychological Bulletin* 82, 213-225.
- Nofsinger, J. R., Sias, R. W., 1999. Herding and feedback trading by institutional and individual investors. *Journal of Finance* 54, 2263-2295.
- Odean, T., 1998. Volume, volatility, price, and profit when all traders are above average. *Journal of Finance* 53, 1887-1934.
- Odean, T., 1999. Do investors trade too much? *American Economic Review* 89, 1279-1298.
- Paek, M., Ko, K., 2014. Aggregate net flows, inflows, and outflows of equity funds: the U.S.

- versus Japan. *Japan and the World Economy* 32, 85-95.
- Phillips, B., Pukthuanthong, K., Rau, P. R., 2016. Past performance may be an illusion: performance, flows, and fees in mutual funds. *Critical Finance Review* 5, 351-398.
- Salganik, G., 2015. The determinants of investment flows: retail versus institutional mutual funds. *Unpublished working paper*. <<http://ssrn.com/abstract=2296508>>.
- Shefrin, H., Statman, M., 1985. The disposition to sell winners too early and rise losers too long. *Journal of Finance* 40, 777-790.
- Sialm, C., Tham, T. M., 2016. Spillover effects in mutual fund companies. *Management Science* 62, 1472-1486.
- Sirri, E. R., Tufano, P., 1998. Costly search and mutual fund flows. *Journal of Finance* 53, 1589-1621.
- Spiegel, M., Zhang, H., 2013. Mutual fund risk and market share adjusted fund flows. *Journal of Financial Economics* 108, 506-528.
- Starks, L. T., Sun, S. Y., 2016. Economic policy uncertainty, learning and incentives: theory and evidence on mutual funds. *Unpublished working paper*. <<http://ssrn.com/abstract=2745711>>.
- Statman, M., Thorley, S., Vorkink, K., 2006. Investor overconfidence and trading volume. *Review of Financial Studies* 19, 1531-1565.
- Taylor, S. E., 1991. Asymmetrical effects of positive and negative events: the mobilization-minimization hypothesis. *Psychological Bulletin* 110, 67-85.
- Thaler, R. H., 2005. *Advances in behavioral finance*, vol. II. Princeton University Press.
- Warther, V. A., 1995. Aggregate mutual fund flows and security returns. *Journal of Financial Economics* 39, 209-235.

Table 1. Descriptive Statistics

This table presents the descriptive statistics of the 1,953 sample funds. Panel A reports the descriptive statistics of 1,659 retail funds (902 retail share classes and 757 exclusive retail funds). Panel B shows the descriptive statistics of 1,196 institutional funds (902 institutional share classes and 294 exclusive institutional funds). Return represents fund returns. Excess return is fund return minus CRSP market return. Net flows are calculated by the method of Huang, Sialm, and Zhang (2011). Size is the total net assets (million dollars). Age represents the number of months since fund inception. Expense ratio includes 12b-1 fees. Load reports the front-end sales loads, and turnover is the CRSP turnover ratio. All figures are computed by a cross-sectional average of time-series averages.

		Return	Excess return	Net flows	Size (million)	Age (month)	Expense ratio	Load	Turnover	No. of Funds
Panel A. Retail Funds										
Retail funds	Average	.0070	-.0002	.0109	1,085	205	.0011	.0088	.8656	1,659
	Median	.0074	-.0003	.0076	182	164	.0011	.0000	.6885	
	Std. dev.	.0034	.0027	.0202	3,816	150	.0004	.0110	.8471	
Retail share class	Average	.0073	.0004	.0111	1,532	226	.0011	.0125	.8104	902
	Median	.0077	-.0002	.0090	271	184	.0012	.0133	.7125	
	Std. dev.	.0028	.0022	.0151	4,848	166	.0003	.0113	.5032	
Exclusive retail funds	Average	.0067	-.0006	.0107	553	180	.0011	.0044	.9327	757
	Median	.0069	-.0005	.0059	107	144	.0011	.0000	.6453	
	Std. dev.	.0040	.0032	.0250	1,884	124	.0004	.0088	1.1289	
Panel B. Institutional Funds										
Institutional funds	Average	.0071	.0002	.0156	529	153	.0008	.0003	.7958	1,196
	Median	.0074	-.0000	.0191	192	143	.0008	.0000	.7082	
	Std. dev.	.0032	.0023	.0197	1,713	78	.0002	.0021	.4997	
Institutional share class	Average	.0072	.0002	.0170	515	159	.0008	.0003	.7911	902
	Median	.0074	-.0000	.0146	196	151	.0008	.0000	.7073	
	Std. dev.	.0031	.0022	.0198	1,837	77	.0002	.0024	.4971	
Exclusive institutional funds	Average	.0069	.0002	.0114	570	137	.0007	.0000	.8109	294
	Median	.0071	.0000	.0102	177	110	.0007	.0000	.7102	
	Std. dev.	.0035	.0025	.0187	1,260	74	.0003	.0005	.5086	

Table 2. Decomposition of Feedback Returns and Net flows

This table shows summary statistics of fund returns and net flows. Panel A presents unexpected market returns and net flows. Panel B presents the fund's excess returns and net flows over the market. Expected market returns and net flows are presented in Panel C.

$$r_{i,t} = (r_{i,t} - r_{s,t}) + (r_{s,t} - r_{m,t}) + (r_{m,t} - E_{t-1}(r_{m,t})) + E_{t-1}(r_{m,t}),$$

$$cf_{i,t}^G = (cf_{i,t}^G - cf_{s,t}^G) + (cf_{s,t}^G - cf_{m,t}^G) + [cf_{m,t}^G - E_{t-1}(cf_{m,t}^G)] + E_{t-1}(cf_{m,t}^G),$$

where $r_{i,t}$ is the return of the i^{th} fund in month t , $r_{m,t}$ is the CRSP market return in month t , $r_{s,t}$ is the return of the s^{th} style group in month t , $E_{t-1}(r_{m,t})$ is the expected market return at the end of month $t-1$, $cf_{i,t}^G$ represents the cash flows of the i^{th} fund included in investor group G in month t , $cf_{m,t}^G$ represents the cash flows included in investor group G in month t , $cf_{s,t}^G$ represents the cash flows of the s^{th} style group of funds included in investor group G in month t , $E_{t-1}(cf_{m,t}^G)$ represents the expected cash flows included in investor group G at the end of month $t-1$, G is retail or institutional fund investors, and S represents growth funds, growth and income funds, or mid- and small-cap funds. The statistics are computed by cross-sectional averages using these monthly average statistics.

	Retail Funds		Institutional Funds	
	Return (%)	Net flows (%)	Return (%)	Net flows (%)
Panel A. Unexpected market returns and corresponding net flows				
	$r_{m,t} - E_{t-1}(r_{m,t})$	$cf_{m,t}^G - E_{t-1}(cf_{m,t}^G)$	$r_{m,t} - E_{t-1}(r_{m,t})$	$cf_{m,t}^G - E_{t-1}(cf_{m,t}^G)$
Average	.0049*** a	-.0039***	.0150***	-.0101***
Median	.0026	-.0029	.0071	-.0085
Std. dev.	.0452	.0054	.0663	.0116
Correlation	.1167***		.0821***	
Panel B. Fund's excess returns over the market and corresponding net flows				
	$r_{i,t} - r_{m,t}$	$cf_{i,t}^G - cf_{m,t}^G$	$r_{i,t} - r_{m,t}$	$cf_{i,t}^G - cf_{m,t}^G$
Average	-.0214***	.9694***	.0170***	.6219***
Median	-.0336	.6946	-.0067	.4706
Std. dev.	.2707	2.0824	.2276	1.9658
Correlation	.0629***		.0223***	
B.1. Style excess returns over the market and corresponding net flows				
	$r_{s,t} - r_{m,t}$	$cf_{s,t}^G - cf_{m,t}^G$	$r_{s,t} - r_{m,t}$	$cf_{s,t}^G - cf_{m,t}^G$
Average	-.0148***	.0274***	-.0026	-.0071
Median	-.0601	-.0225	-.0450	-.0582
Std. dev.	.1123	.1978	.1136	.2004
Correlation	.2393***		.0223***	
B.2. Fund's excess returns over the style group and corresponding net flows				
	$r_{i,t} - r_{s,t}$	$cf_{i,t}^G - cf_{s,t}^G$	$r_{i,t} - r_{s,t}$	$cf_{i,t}^G - cf_{s,t}^G$
Average	-.0066	.9420***	.0196***	.6290***
Median	.0040	.6839	.0208	.5168
Std.	.2336	2.1038	.1881	1.9640
Correlation	.0606***		.0164***	
Panel C. Expected market returns and corresponding net flows				
	$E_{t-1}(r_{m,t})$	$E_{t-1}(cf_{m,t}^G)$	$E_{t-1}(r_{m,t})$	$E_{t-1}(cf_{m,t}^G)$
Average	.7146***	-.0189**	.6854***	.7836***
Median	.7291	.0190	.7121	.7911
Std. dev.	.2914	.3184	.2608	.1645
Correlation	.2161***		.0404***	

a. *, **, ***: indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3. Feedback Trading for Market Timing and Selectivity

This table shows the estimation results of feedback trading for market timing and selectivity. We use 1,659 retail funds and 1,196 institutional funds.

$$\text{BVAR: } \begin{bmatrix} cf_{fb,t}^G \\ r_{fb,t} \end{bmatrix} = \begin{bmatrix} \alpha_{cf}^G \\ \alpha_r \end{bmatrix} + \sum_{k=1}^K \beta_k \begin{bmatrix} cf_{fb,t-k}^G \\ r_{fb,t-k} \end{bmatrix} + \begin{bmatrix} e_{cf,t}^G \\ e_{r,t} \end{bmatrix}, \quad (7)$$

where fb is feedback trading for market timing, selectivity, style selectivity, or fund selectivity; $cf_{fb,t}^G$ represents the feedback cash flows of investor group G in month t; $r_{fb,t}$ is the corresponding feedback return in month t; G is the retail fund group or institutional fund group, and K is the lag-order determined by the Schwarz Bayesian criterion:

$$cf_{fb,t}^G = \begin{cases} (a') \, dcf_{i,m,t}^G = cf_{i,t}^G - cf_{m,t}^G \\ (b') \, dcf_{m,t}^G = cf_{m,t}^G - E_{t-1}(cf_{m,t}^G) \\ (d') \, dcf_{i,s,t}^G = cf_{i,t}^G - cf_{s,t}^G \\ (e') \, dcf_{s,m,t}^G = cf_{s,t}^G - cf_{m,t}^G \end{cases}, \text{ and } r_{fb,t} = \begin{cases} (a) \, dr_{i,m,t} = r_{i,t} - r_{m,t} \\ (b) \, dr_{m,t} = r_{m,t} - E_{t-1}(r_{m,t}) \\ (d) \, dr_{i,s,t} = r_{i,t} - r_{s,t} \\ (e) \, dr_{s,m,t} = r_{s,t} - r_{m,t} \end{cases},$$

where $cf_{i,t}^G$ is the cash flow of the i^{th} fund included in investor group G in month t, $cf_{m,t}^G$ represents the cash flows included in investor group G in month t, $E_{t-1}(cf_{m,t}^G)$ represents the expected cash flows included in investor group G at the end of month t-1, $cf_{s,t}^G$ represents the cash flows of the s^{th} style group of funds included in investor group G in month t, and G is the retail or institutional investors' group. Panels A and B report the test results of feedback trading for market timing and selectivity, respectively. Panels C and D report the test results of feedback trading for style selectivity and fund selectivity among a style group, respectively. The tests in Panels A and C are done at the aggregate market level. In Panels B and D, we report equally weighted averages of statistics because the tests are done at the individual fund level. $\sum \beta$ is the sum of the coefficients of lagged returns ($r_{fb,t-k}$). Num{TNA} of positive (negative) $\sum \beta$ is the proportion of the number of funds {fund size} that are statistically significant and positive (negative) $\sum \beta$. Chi-square statistics are in brackets.

	Retail funds		Institutional funds		
	Coefficient	χ^2	Coefficient	χ^2	
Panel A. Feedback trading for market timing					
$\sum \beta$.0357	[19.29]***a	.0007	[.00]	
Adjusted R ²	.3155		.4156		
Panel B. Feedback trading for selectivity					
Average of $\sum \beta$.2125	[3.16]*	.1348	[1.67]	
Num {TNA} of positive $\sum \beta$		23 {45}% ^b		7 {8}%	
negative $\sum \beta$		1 {0}%		3 {3}%	
Average of Adjusted R ²	.2541		.0859		
Panel C. Feedback trading for style selectivity					
Growth funds	$\sum \beta$.0367	[6.21]**	.0771	[1.20]
	Adjusted R ²	.5792		.0039	
Growth and income funds	$\sum \beta$.0725	[12.10]***	.0090	[.03]
	Adjusted R ²	.6382		.0563	
Mid- and small-cap funds	$\sum \beta$.0706	[12.40]***	.0231	[.93]
	Adjusted R ²	.3709		.0234	
Panel D. Feedback trading for fund selectivity					
Average of $\sum \beta$.2494	[3.02]*	.1181	[1.55]	
Num {TNA} of positive $\sum \beta$		23 {41}%		6 {5}%	
negative $\sum \beta$		1 {1}%		3 {4}%	
Average of Adjusted R ²	.2444		.0830		

a. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

b. The percentage (%) of funds with statistically significant coefficients at the 5% level.

Table 4. Market Timing and Selectivity in Feedback Trading: Exclusive Funds

This table shows the estimation results of feedback trading for market timing and selectivity. We use 757 exclusive retail funds and 294 institutional funds.

$$\text{BVAR: } \begin{bmatrix} cf_{fb,t}^G \\ r_{fb,t} \end{bmatrix} = \begin{bmatrix} \alpha_{cf}^G \\ \alpha_r \end{bmatrix} + \sum_{k=1}^K \beta_k \begin{bmatrix} cf_{fb,t-k}^G \\ r_{fb,t-k} \end{bmatrix} + \begin{bmatrix} e_{cf,t}^G \\ e_{r,t} \end{bmatrix}, \quad (7)$$

where fb is feedback trading for market timing, selectivity, style selectivity, or fund selectivity; $cf_{fb,t}^G$ represents the feedback cash flows of investor group G in month t; $r_{fb,t}$ is the corresponding feedback return in month t, G is the retail fund group or institutional fund group, and K is the lag-order determined by the Schwarz Bayesian criterion:

$$cf_{fb,t}^G = \begin{cases} (a') \, dcf_{i,m,t}^G = cf_{i,t}^G - cf_{m,t}^G \\ (b') \, dcf_{m,t}^G = cf_{m,t}^G - E_{t-1}(cf_{m,t}^G) \\ (d') \, dcf_{i,s,t}^G = cf_{i,t}^G - cf_{s,t}^G \\ (e') \, dcf_{s,m,t}^G = cf_{s,t}^G - cf_{m,t}^G \end{cases}, \text{ and } r_{fb,t} = \begin{cases} (a) \, dr_{i,m,t} = r_{i,t} - r_{m,t} \\ (b) \, dr_{m,t} = r_{m,t} - E_{t-1}(r_{m,t}) \\ (d) \, dr_{i,s,t} = r_{i,t} - r_{s,t} \\ (e) \, dr_{s,m,t} = r_{s,t} - r_{m,t} \end{cases},$$

where $cf_{i,t}^G$ is the cash flow of the i^{th} fund included in investor group G in month t, $cf_{m,t}^G$ represents the cash flows included in investor group G in month t, $E_{t-1}(cf_{m,t}^G)$ represents the expected cash flows included in investor group G at the end of month t-1, $cf_{s,t}^G$ represents the cash flows of the s^{th} style group of funds included in investor group G in month t, and G is the retail or institutional investors' group. Panels A and B report the test results of feedback trading for market timing and selectivity, respectively. Panels C and D report the test results of feedback trading for style selectivity and fund selectivity among a style group, respectively. The tests in Panels A and C are done at the aggregate market level. In Panels B and D, we report equally weighted averages of statistics because the tests are done at the individual fund level. $\sum \beta$ is the sum of the coefficients of lagged returns ($r_{fb,t-k}$). Num{TNA} of positive (negative) $\sum \beta$ is the proportion of the number of funds {fund size} that are statistically significant and positive (negative) $\sum \beta$. Chi-square statistics are in brackets.

	Exclusive Retail Funds		Exclusive Institutional Funds		
	Coefficient	χ^2	Coefficient	χ^2	
Panel A. Feedback trading for market timing					
$\sum \beta$.0416	[10.66]*** ^a	-.0047	[.03]	
Adjusted R ²	.3355		.5160		
Panel B. Feedback trading for selectivity					
Average of $\sum \beta$.2041	[2.98]*	.1098	[1.89]	
Num {TNA} of positive $\sum \beta$		21 {46}% ^b		9 {13}%	
negative $\sum \beta$		9 {1}%		5 {4}%	
Average of Adjusted R ²	.2167		.0926		
Panel C. Feedback trading for style selectivity					
Growth funds	$\sum \beta$.0799	[4.70]**	.1439	[.10]
	Adjusted R ²	.1954		.2962	
Growth and income funds	$\sum \beta$.0950	[19.24]***	-.1256	[.73]
	Adjusted R ²	.3928		.1270	
Mid- and small-cap funds	$\sum \beta$.0505	[5.22]***	-.0001	[.00]
	Adjusted R ²	.2426		.0104	
Panel D. Feedback trading for fund selectivity					
Average of $\sum \beta$.2482	[2.70]	.1500	[1.79]	
Num {TNA} of positive $\sum \beta$		20 {37}%		6 {4}%	
negative $\sum \beta$		0 {2}%		5 {6}%	
Average of Adjusted R ²	.2768		.0919		

a. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

b. The percentage (%) of funds with statistically significant coefficients at the 5% level.

Table 5. Trading Behavior of Retail Investors: Feedback Trading, Overconfidence, and Disposition Effect

This table shows the estimation results of feedback trading for market timing and selectivity. We use 478 exclusive retail funds that are manually matched with EDGAR data.

$$\text{BVAR: } \begin{bmatrix} cf_{fb,t}^G \\ r_{fb,t} \end{bmatrix} = \begin{bmatrix} \alpha_{cf}^G \\ \alpha_r \end{bmatrix} + \sum_{k=1}^K \beta_k \begin{bmatrix} cf_{fb,t-k}^G \\ r_{fb,t-k} \end{bmatrix} + \begin{bmatrix} e_{cf,t}^G \\ e_{r,t} \end{bmatrix}, \quad (7)$$

where fb is feedback trading for market timing, selectivity, style selectivity, or fund selectivity; $cf_{fb,t}^G$ represents the feedback cash flows of investor group G in month t; $r_{fb,t}$ is the corresponding feedback return in month t; G is the retail fund group or institutional fund group; and K is the lag-order determined by the Schwarz Bayesian criterion:

$$cf_{fb,t}^G = \begin{cases} (a') dcf_{i,m,t}^G = cf_{i,t}^G - cf_{m,t}^G \\ (b') dcf_{m,t}^G = cf_{m,t}^G - E_{t-1}(cf_{m,t}^G) \\ (d') dcf_{i,s,t}^G = cf_{i,t}^G - cf_{s,t}^G \\ (e') dcf_{s,m,t}^G = cf_{s,t}^G - cf_{m,t}^G \end{cases}, \text{ and } r_{fb,t} = \begin{cases} (a) dr_{i,m,t} = r_{i,t} - r_{m,t} \\ (b) dr_{m,t} = r_{m,t} - E_{t-1}(r_{m,t}) \\ (d) dr_{i,s,t} = r_{i,t} - r_{s,t} \\ (e) dr_{s,m,t} = r_{s,t} - r_{m,t} \end{cases},$$

where $cf_{i,t}^G$ is the cash flow (total flows, net flows, inflows, and outflows) of the i^{th} fund included in investor group G in month t, $cf_{m,t}^G$ represents the cash flows included in investor group G in month t, $E_{t-1}(cf_{m,t}^G)$ represents the expected cash flows included in investor group G at the end of month t-1, $cf_{s,t}^G$ represents the cash flows of the s^{th} style group of funds included in investor group G in month t, and G is the retail or institutional investors' group. Panels A and B report the test results of feedback trading for market timing and selectivity, respectively. Panels C and D report the test results of feedback trading for style selectivity and fund selectivity among a style group, respectively. The tests in Panels A and C are done at the aggregate market level. In Panels B and D, we report equally weighted averages of statistics because the tests are done at the individual fund level. $\sum \beta$ is the sum of the coefficients of lagged returns ($r_{fb,t-k}$). Num{TNA} of positive (negative) $\sum \beta$ is the proportion of the number of funds {fund size} that are statistically significant and positive (negative) $\sum \beta$. Chi-square statistics are in brackets.

	Total flows		Net flows		Inflows		Outflows		
	Coefficient	χ^2	Coefficient	χ^2	Coefficient	χ^2	Coefficient	χ^2	
Panel A. Feedback trading for market timing									
$\sum \beta$	-0.260	[1.96]	.0283	[8.82]***a	-0.0050	[.22]	-0.0249	[6.27]**	
Adjusted R ²	.1386		.2012		.0878		.2177		
Panel B. Feedback trading for selectivity									
Average of $\sum \beta$.0268	[2.01]	.1351	[3.17]*	.0754	[2.52]	-0.0487	[2.28]	
Num {TNA} of positive $\sum \beta$	10{16}% ^b		24{49}%		14{33}%		3{2}%		
negative $\sum \beta$	5{12}%		1{1}%		3{2}%		14{19}%		
Average of Adjusted R ²	.2761		.2525		.3107		.1901		
Panel C. Feedback trading for style selectivity									
Growth funds	$\sum \beta$.0119	[.06]	.0740	[7.88]***	.0431	[2.14]	-0.0388	[2.38]
	Adjusted R ²	.3923		.5968		.5151		.3483	
Growth and income funds	$\sum \beta$.0414	[1.32]	.0662	[8.05]***	.0487	[5.18]**	-0.0077	[.13]
	Adjusted R ²	.6414		.5818		.6794		.5567	
Mid- and small-cap funds	$\sum \beta$	-0.0202	[.38]	.0783	[7.88]***	.0115	[.23]	-0.0036	[3.06]*

	<i>Adjusted R</i> ²							
	.7504		.4568		.6537		.7124	
Panel D. Feedback trading for fund selectivity								
Average of $\sum\beta$.0283	[1.78]	.1468	[2.99]*	.0890	[2.37]	-.0469	[2.12]
Num {TNA} of positive $\sum\beta$		9{6}%		21{40}%		15{18}%		3{1}%
negative $\sum\beta$		5{13}%		2{3}%		3{3} %		15{30}%
<i>Average of Adjusted R</i> ²	.2768		.2537		.3152		.0915	

a. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

b. The percentage (%) of funds with statistically significant coefficients at the 5% level.

Table 6. Trading Behavior of Institutional Investors: Feedback Trading, Overconfidence, and Disposition Effect

This table shows the estimation results of feedback trading for market timing and selectivity. We use 174 exclusive institutional funds that are manually matched with EDGAR data.

$$\text{BVAR: } \begin{bmatrix} cf_{fb,t}^G \\ r_{fb,t} \end{bmatrix} = \begin{bmatrix} \alpha_{cf}^G \\ \alpha_r \end{bmatrix} + \sum_{k=1}^K \beta_k \begin{bmatrix} cf_{fb,t-k}^G \\ r_{fb,t-k} \end{bmatrix} + \begin{bmatrix} e_{cf,t}^G \\ e_{r,t} \end{bmatrix}, \quad (7)$$

where fb is feedback trading for market timing, selectivity, style selectivity, or fund selectivity; $cf_{fb,t}^G$ represents the feedback cash flows of investor group G in month t; $r_{fb,t}$ is the corresponding feedback return in month t; G is the retail fund group or institutional fund group; and K is the lag-order determined by the Schwarz Bayesian criterion:

$$cf_{fb,t}^G = \begin{cases} (a') dcf_{i,m,t}^G = cf_{i,t}^G - cf_{m,t}^G \\ (b') dcf_{m,t}^G = cf_{m,t}^G - E_{t-1}(cf_{m,t}^G) \\ (d') dcf_{i,s,t}^G = cf_{i,t}^G - cf_{s,t}^G \\ (e') dcf_{s,m,t}^G = cf_{s,t}^G - cf_{m,t}^G \end{cases}, \text{ and } r_{fb,t} = \begin{cases} (a) dr_{i,m,t} = r_{i,t} - r_{m,t} \\ (b) dr_{m,t} = r_{m,t} - E_{t-1}(r_{m,t}) \\ (d) dr_{i,s,t} = r_{i,t} - r_{s,t} \\ (e) dr_{s,m,t} = r_{s,t} - r_{m,t} \end{cases}.$$

where $cf_{i,t}^G$ is the cash flow (total flows, net flows, inflows, and outflows) of the i^{th} fund included in investor group G in month t, $cf_{m,t}^G$ represents the cash flows included in investor group G in month t, $E_{t-1}(cf_{m,t}^G)$ represents the expected cash flows included in investor group G at the end of month t-1, $cf_{s,t}^G$ represents the cash flows of the s^{th} style group of funds included in investor group G in month t, and G is the retail or institutional investors' group. Panels A and B report the test results of feedback trading for market timing and selectivity, respectively. Panels C and D report the test results of feedback trading for style selectivity and fund selectivity among a style group, respectively. The tests in Panels A and C are done at the aggregate market level. In Panels B and D, we report equally weighted averages of statistics because the tests are done at the individual fund level. $\sum \beta$ is the sum of the coefficients of lagged returns ($r_{fb,t-k}$). Num{TNA} of positive (negative) $\sum \beta$ is the proportion of the number of funds {fund size} that are statistically significant and positive (negative) $\sum \beta$. Chi-square statistics are in brackets.

	Total flows		Net flows		Inflows		Outflows		
	Coefficient	χ^2	Coefficient	χ^2	Coefficient	χ^2	Coefficient	χ^2	
Panel A. Feedback trading for market timing									
$\sum \beta$	-0.0394	[1.29]	.0074	[.06]	-.0247	[.69]	-.0366	[1.15]	
Adjusted R^2	.2629		.2637		.2359		.2652		
Panel B. Feedback trading for selectivity									
Average of $\sum \beta$.1315	[1.53]	.2204	[2.00]	.1633	[1.89]	-.0409	[1.33]	
Num {TNA} of positive $\sum \beta$	8 {7}% ^b		13 {10}%		10 {10}%		7 {7}%		
negative $\sum \beta$	3 {2}%		6 {9}%		5 {6}%		3 {1}%		
Average of Adjusted R^2	.0839		.1183		.1313		.0604		
Panel C. Feedback trading for style selectivity									
Growth funds	$\sum \beta$	-0.0372	[.17]	.0515	[.98]	.0157	[.12]	-.0429	[.93]
	Adjusted R^2	.1399		.0679		.1167		.0179	
Growth and income funds	$\sum \beta$.0560	[.32]	-.0418	[.29]	.0317	[.26]	.0471	[.52]
	Adjusted R^2	.1609		.0425		.1703		.0613	

Mid- and small-cap funds	$\sum\beta$.0680	[2.30]	-.0419	[1.47]	.0162	[.38]	.0559	[3.37]*
	<i>Adjusted R</i> ²	.2503		.0592		.2376		.1301	
Panel D. Feedback trading for fund selectivity									
	Average of $\sum\beta$.0969	[1.74]	.2120	[2.01]	.1604	[1.71]	-.0571	[1.34]
	Num {TNA} of positive $\sum\beta$		6{4}%		10{5}%		7{6}%		5{8}%
	negative $\sum\beta$		5{4}%		6{11}%		4{6}%		7{5}%
	<i>Average of Adjusted R</i> ²	.0850		.1137		.1204		.0665	

a. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

b. The percentage (%) of funds with statistically significant coefficients at the 5% level.

Table 7. Attribution Bias for Retail Funds with Positive Feedback

This table presents the effect of self-attribution bias on feedback trading for retail funds. The sample funds in this analysis are retail funds that engage in positive feedback trading in Table 3. The self-attribution bias is estimated as follows.

$$Skill_t = cf_{fb,t-T:t-1} \times r_{fb,t-T:t-1}, \quad (8)$$

where $Skill_t > 0$ ($Skill_t \leq 0$) means the investment success (failure) of retail investors, $cf_{fb,t}$ represents the net flows of retail investors in month t, and T is the past investment period (T = 1 and 3 months). Chi-square statistics are in brackets.

$$cf_{fb,t} = \alpha_{cf} + \sum_{k=1}^K \beta_k r_{fb,t-k} I(Skill_t > 0) + \sum_{k=1}^K \delta_k r_{fb,t-k} I(Skill_t \leq 0) + \sum_{k=1}^K \gamma_k cf_{fb,t-k} + e_{cf}, \quad (9)$$

$I(Skill_t > 0)$ equals 1 if $Skill_t > 0$, and 0, otherwise, $I(Skill_t \leq 0)$ equals 1 if $Skill_t \leq 0$, and 0, otherwise.

Positive $\sum \beta$ indicates that the positive feedback trading is caused by self-enhancing bias, and positive $\sum \delta$ indicates that the positive feedback trading is caused by self-protective bias.

	1 Month		3 Months	
Panel A. Feedback trading for market timing				
Self-enhancing bias ($\sum \beta$)	.0424	[13.71]***a	.0432	[13.61]***
Self-protective bias ($\sum \delta$)	.0282	[5.50]**	.0329	[11.97]***
<i>Difference</i> ($H_0: \sum \beta - \sum \delta = 0$)	.0142	[.72]	.0103	[.60]
<i>Adjusted R²</i>	.3115		.3149	
Panel B. Feedback trading for selectivity				
Self-enhancing bias ($\sum \beta$)	.6252	[10.75]***	.5423	[6.75]***
Self-protective bias ($\sum \delta$)	.1477	[2.69]	.2577	[5.37]**
<i>Difference</i> ($H_0: \sum \beta - \sum \delta = 0$)	.4775	[4.26]**	.2846	[4.83]**
<i>Average of Adjusted R²</i>	.3873		.3702	
Panel C. Feedback trading for style selectivity				
<u>Growth funds</u>				
Self-enhancing bias ($\sum \beta$)	.0877	[9.64]***	.0444	[8.91]***
Self-protective bias ($\sum \delta$)	.0143	[.13]	.0079	[.28]
<i>Difference</i> ($H_0: \sum \beta - \sum \delta = 0$)	.0734	[2.04]	.0365	[1.06]
<i>Adjusted R²</i>	.6042		.6006	
<u>Growth and income funds</u>				
Self-enhancing bias ($\sum \beta$)	.0890	[6.64]***	.0871	[14.39]***
Self-protective bias ($\sum \delta$)	.0519	[2.94]*	.0126	[.07]
<i>Difference</i> ($H_0: \sum \beta - \sum \delta = 0$)	.0371	[.40]	.0745	[2.04]
<i>Adjusted R²</i>	.6366		.6385	
<u>Mid- and small-cap funds</u>				
Self-enhancing bias ($\sum \beta$)	.0737	[5.58]**	.0901	[16.86]***
Self-protective bias ($\sum \delta$)	.0665	[3.35]*	-.0021	[.00]
<i>Difference</i> ($H_0: \sum \beta - \sum \delta = 0$)	.0072	[.08]	.0880	[2.96]*
<i>Adjusted R²</i>	.3681		.3848	
Panel D. Feedback trading for fund selectivity				
Self-enhancing bias ($\sum \beta$)	.7348	[10.06]***	.5981	[6.66]***
Self-protective bias ($\sum \delta$)	.1917	[2.67]	.3249	[4.27]**
<i>Difference</i> ($H_0: \sum \beta - \sum \delta = 0$)	.5431	[3.97]**	.2732	[2.19]
<i>Average of Adjusted R²</i>	.3902		.3772	

a. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 8. Market Conditions and Feedback Trading for Retail Investors

This table presents feedback trading behaviors in different market conditions.

$$cf_{fb,t} = \alpha_{cf} + \sum_{k=1}^K \beta_k r_{fb,t-k} I(bull_t) + \sum_{k=1}^K \delta_k r_{fb,t-k} I(bear_t) + \sum_{k=1}^K \gamma_k cf_{fb,t-k} + e_{cf} \quad (10)$$

where $I(bull_t)$ equals 1 if month t is in an up market and 0 otherwise, $I(bear_t)$ equals 1 if month t is in a down market and 0 otherwise, fb is feedback trading for market timing and selectivity, $cf_{fb,t}^G$ represents the feedback cash flows of investor group G in month t , and $r_{fb,t}$ is the corresponding feedback return in month t . If $\sum \beta > 0$ ($\sum \delta > 0$), this means positive feedback trading in a bull (bear) market; $cf_{fb,t}$ is net flows of retail investors in month t . The periods of bull market are 1995–1998, 2003–2006, 2009, and 2012–2013, and the periods of bear market are 1999–2002, 2007–2008, and 2010–2011. The tests in Panels A and C are done at the aggregate market level. In Panels B and D, we report equally weighted averages of statistics because the tests are done at the individual fund level. $\sum \beta$ and $\sum \delta$ are the sums of the coefficients of lagged returns ($r_{fb,t-k}$) in a bull market and a bear market, respectively. Num{TNA} of positive (negative) sum of coefficients is the proportion of the number of funds {fund size} that have a statistically significant and positive (negative) sum of coefficients. Chi-square statistics are in brackets.

	Bull Market		Bear Market		
	$\sum \beta$	χ^2	$\sum \delta$	χ^2	
Panel A. Feedback trading for market timing					
Sum of coef.	.0413	[10.86]***a	.0305	[9.27]***	
<i>Adjusted R²</i>		.3241			
Panel B. Feedback trading for selectivity					
Average of the sum of coef.	.3060	[1.91]	.2413	[2.53]	
Num{TNA} of positive sum of coef.		9 {15}% ^b		15 {27}%	
negative sum of coef.		0 {0}%		1 {1}%	
<i>Average of Adjusted R²</i>		.2477			
Panel C. Feedback trading for style selectivity					
Growth funds	Sum of coef.	.0318	[2.03]	.0405	[4.34]**
	<i>Adjusted R²</i>		.5774		
Growth and income funds	Sum of coef.	.0228	[.32]	.0799	[12.36]***
	<i>Adjusted R²</i>		.6381		
Mid- and small-cap funds	Sum of coef.	.0846	[6.38]**	.0635	[6.92]***
	<i>Adjusted R²</i>		.3688		
Panel D. Feedback trading for fund selectivity					
Average of the sum of coef.	.2204	[1.92]	.2198	[2.61]	
Num{TNA} of positive sum of coef.		9 {17}%		14 {28}%	
negative sum of coef.		1 {0}%		1 {0}%	
<i>Average of Adjusted R²</i>		.2576			

a. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

b. The percentage (%) of funds with statistically significant coefficients at the 5% level.

Figure 1. Size of Sample Funds and Cumulative Stock Market Returns

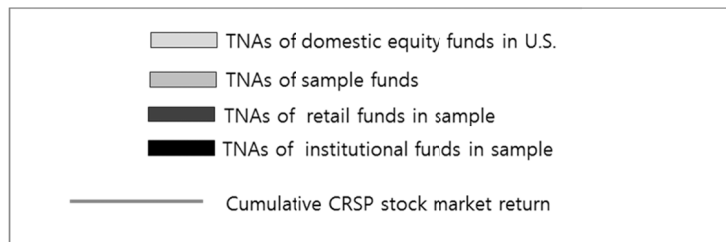
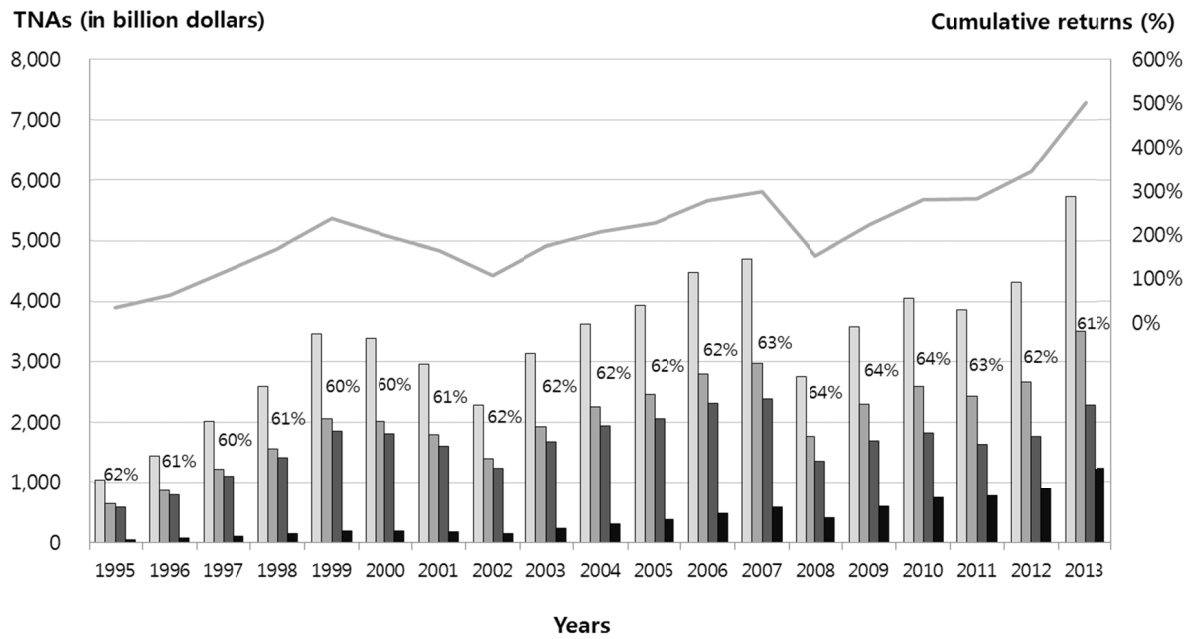


Figure 2. Cumulative Impulse-response Function: Feedback Trading for Market Timing

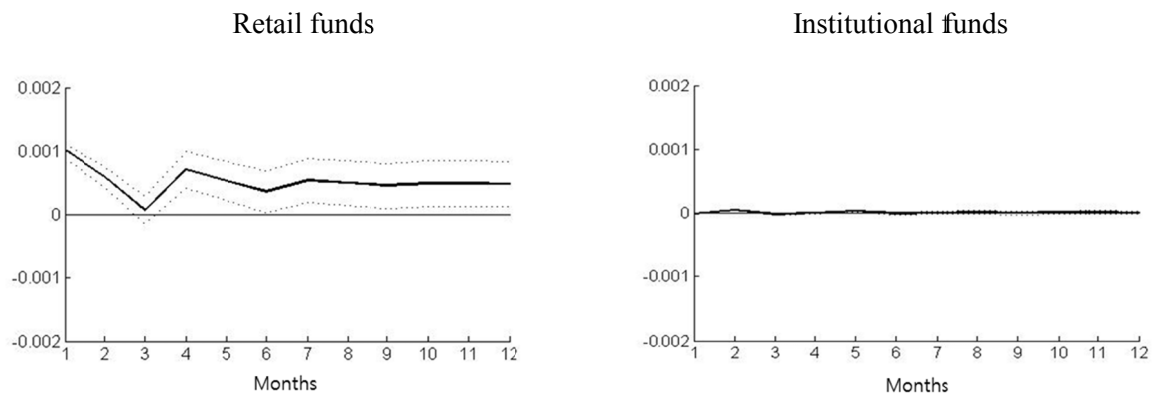
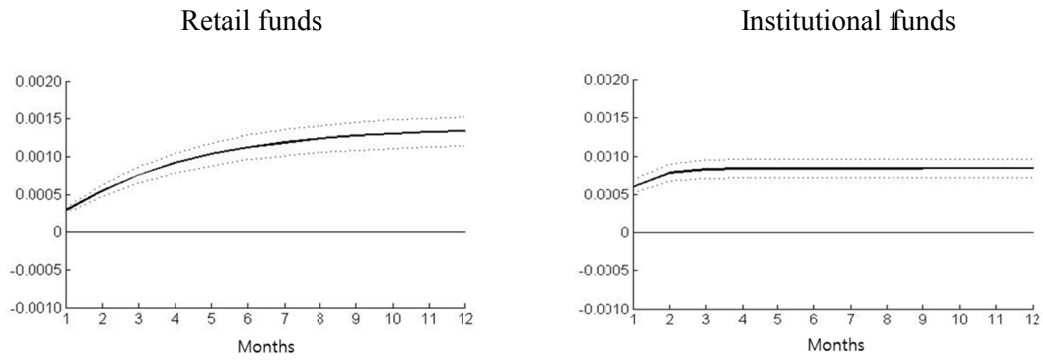
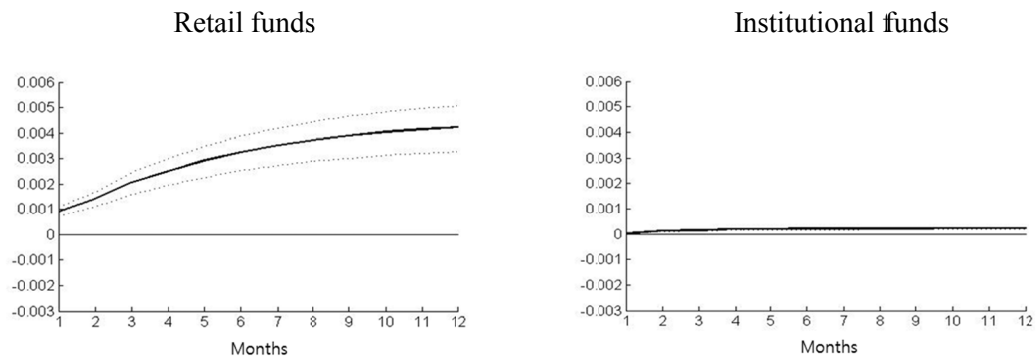


Figure 3. Cumulative Impulse-response Function: Feedback Trading for Style Selectivity

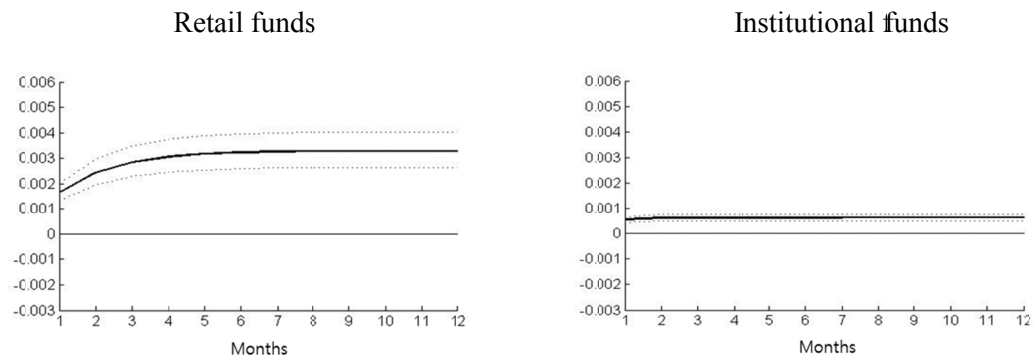
Panel A. Growth funds



Panel B. Growth and income funds



Panel C. Mid- and small-cap funds



<Appendix A>

Table A1. Previous Studies on Investors' Trading Behavior

Trading Behavior	Mutual Fund Studies	Non-mutual Fund Studies	
		Under-reaction and over-reaction	Behavioral approach
Feedback trading	<p>Aggregate fund level: Warther (1995); Fant (1999); Edelen (1999); Cao, Chang, and Wang (2008); Jank (2012); Paek and Ko (2014)</p> <p>Individual fund level: Ippolito (1992); Chevalier and Ellison (1997); Sirri and Tufano (1998); Edelen (1999); Fant and O'Neal (1999); Lynch and Musto (2003); Huang, Wei, and Yan (2007); Ivkovic and Weisbenner (2009); Spiegel and Zhang (2013); Franzoni and Schmalz (2013); Starks and Sun (2016)</p> <p>Fund family level: Brown and Wu (2016); Phillips, Pukthuanthong, and Rau (2016); Sialm and Tham (2016)</p>	<p>Overreaction: DeLong, Shleifer, Summers, and Waldmann (1990); Lo and MacKinlay (1990); Guo and Ou-Yang (2015)</p> <p>Initial underreaction and overreaction: Hong and Stein (1999); Hong, Lim, and Stein (2000); Edmans, Goldstein, and Jiang (2015)</p> <p>Herding: Nofsinger and Sias (1999)</p>	<p>Conservatism and representative bias: Griffin and Tversky (1992); Barberis, Shleifer, and Vishnya (1998); Barberis and Thaler (2003); Thaler (2005)</p> <p>Representative bias and excessive optimism to overreaction: De Bondt and Thaler (1985, 1987)</p>
Overconfidence	<p>Behavioral biases: Bailey, Kumar, and Ng (2011)</p>	<p>Institution's overconfidence and feedback trading: Kim and Nofsinger (2007); Chuang and Susmel (2011)</p>	<p>Attribution bias: Daniel, Hirshleifer, and Subrahmanyam (1998); Odean (1998, 1999); Gervais and Odean (2001); Statman, Thorley, and Vorkink (2006)</p>
Disposition effect	<p>Behavioral biases: Bailey, Kumar, and Ng (2011)</p>	<p>Frazzini (2006) Birru (2015)</p>	<p>Shefrin and Statman (1985); Barberis and Xiong (2009)</p>