Is Investor Rationality Time Varying? Evidence from the Mutual Fund Industry*

Vincent Glode, Burton Hollifield, Marcin Kacperczyk, and Shimon Kogan

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*Glode is at the Wharton School, University of Pennsylvania. Hollifield is at Carnegie Mellon University. Kacperczyk is at New York University and NBER. Kogan is at the University of Texas at Austin. We thank Amit Seru for comments on an earlier draft of the paper. We also thank Michael Cooper, Rick Green, Philipp Schnabl, Clemens Sialm, Stijn van Nieuwerburgh, seminar participants at Bank of America, the Interdisciplinary Center Herzliya (IDC), New York University, Tel-Aviv University, Texas A&M University, University of Michigan, University of Texas at Austin, and University of Utah for useful comments. Vincent Glode gratefully acknowledges financial support from the Social Sciences and Humanities Research Council of Canada, the William Larimer Mellon fund, and the Center for Financial Markets. Hollifield thanks National Science Foundation grant 0624351 for support. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation.

Abstract

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Evidence from the Mutual Fund Industry

We provide new empirical evidence suggesting that the marginal investor in mutual funds behaves differently across market conditions. If the marginal investor allocates capital across mutual funds rationally, then the relative performance of funds should be unpredictable. We find that relative fund performance is predictable after periods of high market returns but not after periods of low market returns. The asymmetric predictability in performance we document cannot be explained by time-varying differences in transaction costs or style exposures between funds, or by sample selection. Consistent with the hypothesis that the asymmetric predictability in performance may be driven by unsophisticated investors' mistakes when allocating capital, we document that performance predictability is more pronounced for funds that cater to retail investors than for funds that cater to institutional investors.

JEL classification: G23, G11, G14.

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1 Introduction

Traditional asset pricing models typically assume that marginal investors always behave rationally. But a number of studies document substantial deviations from rationality in the behavior of some investors across different market conditions. For example, Grinblatt and Keloharju (2001), Lamont and Thaler (2003), Brunnermeier and Nagel (2004), and Cooper, Gutierrez, and Hameed (2004) find indirect evidence that unsophisticated investors are more likely to enter the stock market when market returns are high. Seru, Shumway, and Stoffman (2009) document that unsophisticated investors learn more and make fewer mistakes in periods of low market returns. But what about the marginal investors? Do they always behave rationally or do they behave less rationally in specific market conditions?

We provide new empirical evidence of deviations of marginal investors' decisions from a rational benchmark model. We focus on the U.S. mutual fund industry to study investors' behavior because the fund industry is large and economically important. By the end of 2007, 44 percent of U.S. households owned mutual fund shares and invested a total of 12 trillion dollars in U.S. mutual funds. During the same year, a record-high 883 billion dollars flowed into U.S. mutual funds.[1]

To identify deviations from rational behavior by marginal investors, we use the Berk and Green (2004) model of the mutual fund industry as a benchmark for a rational equilibrium in the mutual fund industry. The model shows that if asset management has decreasing returns to scale as empirically suggested by Chen et al. (2004) and Edelen, Evans, and Kadlec (2007) and if fund investors are rational, then fund flows should adjust and equalize expected performance across funds, thus resulting in no predictability of relative fund performance. Consequently, the empirical relationship between fund flows, past abnormal returns, and future abnormal returns across funds should be informative about the rationality of the marginal fund investor's decisions.

[1]See, the 2008 Investment Company Factbook (http://www.icifactbook.org.)

We study the marginal investors' rationality using a large sample of mutual funds from the 1980–2005 period. We establish that mutual fund flows are sensitive to funds' past performance, consistent with Chevalier and Ellison (1997), among others. Similar to Carhart (1997), we sort funds into performance quintiles and track their subsequent performance. After periods of high market returns, the subsequent ranking of portfolios is preserved for at least twelve months and the spread in four-factor alphas between high- and low-performance portfolios is about 1.7% on an annualized basis. After periods of low market returns, the performance ranking changes and the spread in four-factor alphas between high- and low-performance portfolios is about zero. Relative performance is persistent after periods of high market returns but not after periods of low market returns.

We observe a qualitatively similar pattern when we sort funds based on past fund flows. Building on existing empirical evidence (e.g., Gruber (1996) and Zheng (1999)) suggesting that funds with high past flows perform better than funds with low past flows in a given month, we separate funds that receive flows above the median from funds that receive flows below the median of the distribution of fund flows in that month. The portfolio of high-flow funds would have earned 1.2% to 2.5% higher annualized abnormal return than the portfolio of low-flow funds after periods of high market returns. But both portfoliolos would have earned practically the same return after periods of low market returns.

Our results are more pronounced when we look at holding-period horizons beyond one month and they are robust to the inclusion of momentum and liquidity factors, time-varying factor loadings, and variations in the definitions of market conditions and fund-flow cutoffs. Our results suggest that after high market returns, investors could increase their expected abnormal returns by moving their capital from funds with poor past performance and relatively low flows to funds with good past performance and relatively high flows.

We explore a number of explanations for our findings. First, the marginal mutual fund investor may be subject to asymmetric trading frictions in up and down markets, leading her to rationally refrain from switching funds. Most trading frictions, such as load fees and lock-ins, appear to be either non-binding for at least one marginal investor or to be constant across market conditions. Another friction is capital gains taxes—investors may be reluctant to switch capital across funds, especially when realized returns are high or in good market conditions. Using fund turnover and momentum as proxies for the average effective capital gains tax liability, we find only weak support for the hypothesis that taxes can explain our results.

Second, the patterns in performance predictability we find could be an artifact of a particular correlation structure between the returns on our switching strategy and those on a common passive strategy. For example, if high-flow funds were value funds and low-flow funds were growth funds, switching between the two types of funds would be equivalent to investors following a value strategy. To the extent that the profitability of the value strategy was high in up markets and zero in down markets, we would obtain observationally equivalent results to ours. To explore such an alternative, we calculate time-varying gains to predictability within various commonly used investment styles. We find evidence of performance predictability within each style category, which suggests that our findings are unlikely to result from mechanically following a common, passive investment strategy.

Third, we find evidence that our findings do not result from time-varying differences in a survivorship bias between funds in a high-flow portfolio and those in a low-flow portfolio.

Finally, we provide suggestive evidence that the observed asymmetry in performance predictability may be due to capital allocation mistakes by retail investors. We conjecture that individual investors should be more subject to behavioral biases than institutional investors. Consistent with our hypothesis, we find that the asymmetry in performance predictability is concentrated among funds that cater to retail investors. We also find that performance predictability is substantially stronger for young funds, consistent with the idea that young funds cater to less sophisticated investors.

We argue that the observed changes in investors' rationality may affect fund managers' behavior. After periods of high market returns, the marginal fund investor does not seem to process information efficiently, and thus the incentives to exert costly effort and acquire information about investment opportunities should be weaker for fund managers. To test the hypothesis, we look at how cross-sectionally distinct the fund managers' investment strategies are across market conditions. Based on activeness measures similar to those in Chevalier and Ellison (1999), fund managers are more active after periods of low market returns than after periods of high market returns. If the fund managers' activeness is costly, then the fund managers' increased activeness after periods of low market returns may be a rational response to an increase in the fund flows' sophistication after periods of low market returns.

Our results are related to several strands of literature. First, they contribute to the growing empirical work on individuals' trading behavior. For example, Odean (1999) and Barber and Odean (2001) conclude that investors with discount brokerage accounts trade excessively as their realized returns tend to decrease with trading. Poteshman and Serbin (2003) find evidence of irrational, early exercise in exchange-traded stock options by customers of discount brokers or full-service brokers. We find evidence that casts doubt on the rationality of retail mutual fund investors, particularly after periods of high market returns.

Second, our work is also related to a number of studies that document the influence of unsophisticated investors on equilibrium asset pricing. Using the trade data from Chicago Board of Trade, Coval and Shumway (2005) find that behavioral biases can have consequences for the trading and pricing of futures contracts, and Barber, Odean, and Zhu (2006) find that stocks heavily bought by individual investors in one week earn high returns in the subsequent week, while stocks heavily sold in one week earn low returns in the subsequent week. Our results show that rationality may need to be evaluated in a framework that accounts for market conditions.

Third, we contribute to the literature on smart money in mutual funds. Gruber (1996) and Zheng (1999) argue that fund flows tend to predict future fund performance, the effect called the smart-money effect. Subsequently, Wermers (2003) and Sapp and Tiwari (2004) cast doubt on the finding by showing that smart money is largely a momentum-driven phenomenon. Using the stock-level data based on mutual fund holdings, Frazzini and Lamont (2008) document that the smart-money effect is very short lasting and that if anything, money is dumb. Our view of the smart money effect is different. We evaluate smart money through the lens of a rational equilibrium model, and provide evidence that points to the importance of market conditions for evaluating the rationality of fund flows.

Finally, our empirical results also add to the discussion on the value of active management. Carhart (1997) documents that active mutual funds do not outperform passive benchmarks. He also shows that fund performance is hard to predict – a finding challenged by other studies which argue that traditional measures of performance may be too noisy as predictive variables (e.g., Cohen, Coval, and Pástor (2005), Kacperczyk and Seru (2007), and Kacperczyk, Sialm, and Zheng (2008)). We show that even the standard measures of performance may have predictive power if we restrict the analysis to certain states of the economy. We provide an economic rationale for the finding.

2 Theoretical Framework and Predictions

Our null hypothesis is that marginal investors' decisions are always rational. We use the rational model of mutual fund investment in Berk and Green (2004) to provide a benchmark for our empirical work (see also Nanda, Narayanan, and Warther (2000)). Berk and Green (2004) study an economy with a competitive supply of capital by investors, differential ability levels across fund managers, and learning about managers' ability to generate high returns based on past returns.

Let $R^G_{i,t+1}$ be fund i's return gross of expenses and fees between time t and $t+1$, and let $q_{i,t}$ be fund i's size at time t. The fund manager i charges a fee of $f_{i,t}$ per dollar to manage the fund. Consistent with empirical findings by Chen et al. (2004) and Edelen, Evans, and Kadlec (2007), generating positive abnormal returns becomes more difficult as the size of the assets under management increases. Assuming that fund managers have no capital, fund investors are the ones paying the fee and the cost from diseconomies of scale, which is represented by $C(q_{i,t})$, and therefore fund investors receive the net return, $R_{i,t+1}$:

$$R_{i,t+1} = R^G_{i,t+1} - \frac{C(q_{i,t})}{q_{i,t}} - f_{i,t}. \tag{1}$$

We refer to $\frac{C(q_{i,t})}{q_{i,t}}$ as the average cost of actively managing the fund between time t and $t+1$. As in Berk and Green (2004), the cost function C is assumed to be strictly increasing and strictly convex, implying that the average cost is increasing in fund size, consistent with findings of diseconomies of scale in asset management by Chen et al. (2004) and Edelen, Evans, and Kadlec (2007).

For each fund i, there is a passive benchmark portfolio with a return of:

$$R^B_{i,t+1} = R_{F,t} + \sum_{k=1}^{K} \beta_{k,i} F_{k,t+1}, \tag{2}$$

where $R_{F,t}$ is the risk-free rate known at time t for the period between t and $t+1$, $F_{k,t+1}$ is the excess return on the k^{th} factor-mimicking portfolio, and $\beta_{i,k}$ for $k = 1, ..., K$ are the factor loadings of the fund's returns against the factor-mimicking portfolios. The net return in excess of the benchmark return is:

$$\begin{aligned} \alpha_{i,t+1} + \epsilon_{i,t+1} &= R_{i,t+1} - R^B_{i,t+1} \\ &= R^G_{i,t+1} - \frac{C(q_{i,t})}{q_{i,t}} - f_{i,t} - R^B_{i,t+1}. \end{aligned} \tag{3}$$

Under a competitive supply of capital by investors to mutual funds, the fund size and its fee should adjust so that investors are indifferent between investing in the mutual fund and the benchmark portfolio. Therefore:

$$E_t \left[\alpha_{i,t+1} + \epsilon_{i,t+1}\right] = 0, \tag{4}$$

where E_t denotes investors' expectation, conditional on all information available to the investors at time t.

Using equation (3), the competitive supply condition implies that the expected gross return in excess of the benchmark return should be equal to the fee plus the average cost:

$$E_t \left[R^G_{i,t+1} - R^B_{i,t+1}\right] = \frac{C(q_{i,t})}{q_{i,t}} + f_{i,t}. \tag{5}$$

Berk and Green (2004) consider an environment in which investors learn about the fund manager's ability from the returns generated in the past. When investors observe a fund returns, they update their beliefs about the manager's ability to produce excess returns in the future. Given the competitive supply condition in equation (5), the fund's cost or fee must adjust as investors update their beliefs. Empirically, fund fees tend to exhibit very little time-series variation (see, e.g., Christoffersen (2001)). If the fund manager does not increase the fee, then fund size will increase causing an increase in the average cost until equation (5) is satisfied. Berk and Green (2004) argue that such a mechanism can help explain why investors appear to chase fund performance, despite the fact that abnormal performance does not persist.

The main implication of the Berk and Green (2004) model for us is that future relative performance should not be predictable using information available to investors. Fund size adjusts to make expected abnormal returns equal across all funds. Fund flows reflect investors' decisions, and therefore provide a useful empirical instrument: If the reaction of fund flows to performance changes with market conditions, then accounting for market conditions should provide power to our empirical tests on the predictability of mutual fund performance.

The no-predictability result is not specific to Berk and Green (2004). A classic market efficiency argument suggests that predictability in abnormal returns, whether it is in the context of mutual funds, equity shares or bonds, should disappear before financial markets can reach an equilibrium. Berk and Green (2004) provide us with the mechanisms that describe how such an equilibrium should be reached in the open-end mutual fund industry. The absence of predictability in abnormal performance in equilibrium holds, however, in virtually any environment where the marginal investor behaves rationally.

In our empirical tests, we aim to identify situations in which the supply of investors' capital to mutual funds is such that condition (5) does not hold. For example, we could think of a situation in which a large number of investors participating in the mutual fund sector do not behave in a fully rational manner. Suppose that such investors were not responsive enough to information about past performance, relative to a fully rational setting. Then, fund size would not be sensitive enough to past performance and, consequently, mutual funds with good performance in one period would stay too small, their costs would be too small, and these funds would offer a positive expected abnormal return:

$$E_t\left[\alpha_{i,t+1} + \epsilon_{i,t+1}\right] > 0. \tag{6}$$

Similarly, funds with poor performance in one period would stay too big, their costs would be too large, and these funds would offer a negative expected abnormal return:

$$E_t\left[\alpha_{i,t+1} + \epsilon_{i,t+1}\right] < 0. \tag{7}$$

In such a situation, abnormal returns would tend to persist over time, unlike the prediction of the Berk and Green (2004) model.

If fund performance depends on the fund manager's effort as well as ability, then any information that is useful at predicting effort, will also provide predictive power for abnormal returns. We use this insight to guide our choice of instruments. We also show that market conditions are useful at predicting measures of fund manager's activeness.

3 Data

We define three market conditions: Up, Mid, and Down. An up market is when the three-month moving average of the market excess returns for this time period is higher than its historical 75th percentile. A mid market is when the three-month moving average of the market excess returns for this time period is higher than its historical 25th percentile and lower than its historical 75th percentile. A down market is when the three-month moving average of the market excess returns for this time period is lower than its historical 25th percentile. Historical percentiles for time period t are based on the three-month moving average of S&P 500 index returns from quarter three of 1926 up to period t. We denote the associated indicator functions with $I(MKT_t = Up)$, $I(MKT_t = Mid)$, and $I(MKT_t = Down)$. Our results are robust to the use of alternative definitions of market conditions such as different percentile cutoffs or longer-term averages of market returns.

We use monthly data over the period 1980 to 2005. The sample spans 309 months, out of which 39 months are defined as up markets and 38 months are defined as down markets. The remaining 232 months are mid-market observations. Market conditions tend to cluster over time, as illustrated by the transition probabilities in Table 1. Figure 1 presents the evolution of market conditions over time along with market returns. The shaded areas in each panel indicate when each particular market condition is attained. Table 2 provides summary statistics of key variables for the different market conditions. The average market return is 4.8% in up markets and –3.0% in down markets.

To construct our sample of funds, we merge the CRSP Survivorship Bias Free Mutual Fund Database with the Thompson Financial CDA/Spectrum holdings database and the CRSP stock price data using the methodology of Kacperczyk, Sialm, and Zheng (2008). The

CRSP mutual fund database includes information on fund returns, total net assets, different types of fees, investment objectives, and other fund characteristics. The CDA/Spectrum database provides stock holdings of mutual funds. These data are collected both from reports filed by mutual funds with the SEC and from voluntary reports generated by the funds. We also link reported stock holdings to the CRSP stock database to obtain further information.

We focus our analysis on domestic open-end diversified equity mutual funds, for which the holdings data are most complete and reliable. We therefore eliminate from our sample balanced, bond, money market, international, sector, and index funds, as well as funds not invested primarily in equity securities. We also exclude funds that hold less than 10 stocks, funds that invest less than 80% of their assets in equity, and funds that in the previous month managed less than $5 million. We also aggregate funds with multiple share classes into portfolios by value-weighing each share class. Appendix A provides further details on the sample selection. Overall, our sample includes 3,477 distinct funds and 250,219 fund-month observations. The number of funds in each month varies from 158 in May 1980 to 1,670 in July 2001.

Here, we define the other variables that we use in our tests. We add the subscripts i, t on a variable to refer to fund i over period t. But in order to reduce notational clutter, we only use subscripts when necessary for expositional purposes.

Flow is the fund flow defined as the growth rate of the assets under management (*TNA*), after adjusting for the appreciation of the mutual fund's assets (R), assuming that all cash flows are invested at the end of the period:

$$Flow_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1} * (1 + R_{i,t})}{TNA_{i,t-1}}. \tag{8}$$

R is the fund's monthly return net of expenses. To measure *Performance*, we use the factor loadings estimated from a 36-month rolling regression of a fund's returns on market premium, size, value, and momentum factors and we subtract the required return, given these loadings, from the fund's realized return. *TNA* is the fund's total net assets in $ millions. *Expenses* is the fund's expense ratio. *Turnover* is the fund's turnover ratio. *Load* is the total load fee. *Value* is the average score of all stocks in the fund's portfolio, where each stock is assigned a score from 1 to 5 based on its book-to-market ratio. *Size* is the average score of all stocks in the fund's portfolio, where each stock is assigned a score from 1 to 5 based on its market capitalization. *Momentum* is the average score of all stocks in the fund's portfolio, where each stock is assigned a score from 1 to 5 based on its past 12-month returns.

Beta Deviation is the absolute value of the difference between fund i's beta in month t and the average beta in that month of all funds in the fund's objective class. Individual fund beta is a market beta from a four-factor model calculated using 36 months of past returns. *Sector Deviation* is the mean square root of the sum of squared differences between the share of fund i's assets in each of 10 industry sectors of Fama and French (1997) and the mean share in each sector in month t among all funds in the fund's objective class (aggressive growth, growth, or value). *Unsystematic Deviation* is the absolute value of the difference between fund i's unsystematic risk, *Unsystematic Risk*, and the sample average of this variable over all funds in the fund's objective class in month t. *Unsystematic Risk* is the absolute value of the residual from the four-factor model of Carhart (1997).

Table 2 reports summary statistics for these variables; Panel A for the entire sample, Panel B for up markets only, and Panel C for up markets only. Most of the numbers in the unconditional sample are consistent with those reported in previous studies, which gives us confidence that our analysis is not biased due to sample selection.

Mutual funds in our sample tend to receive more flows after high market returns but do not necessarily perform better on a risk-adjusted basis. Most other variables do not vary much across the two market conditions, except for measures of deviation, which tend to be higher in down markets. We defer the specific explanation of these results to later sections.

4 Predictability of Fund Flows and Returns

4.1 The Conditional Flow-Performance Relationship

The model of rational fund flows in Berk and Green (2004) assumes that investors are Bayesian and learn about managerial ability from a fund's past returns. The equilibrium behavior by such investors is to adjust their capital flows rationally based on past performance. Such learning implies that fund flows should be positively related to past fund performance. Here, we evaluate how investors' reaction to fund performance changes with market conditions.

We run a regression in which we relate *Flow* to *Performance* and study the interaction of *Performance* with indicator functions for market conditions:[2]

$$\begin{aligned} Flow_{i,t+1} &= \gamma_0 + \sum_{z \in \{Up, Down\}} \gamma_1^z I(MKT_t = z) \\ &+ \sum_{z \in \{Up, Down\}} \gamma_2^z I(MKT_t = z) Performance_t^i + \gamma_3 X_t^i + Fund F.E. + \epsilon_{t+1}^i, \end{aligned} \quad (9)$$

where $I(MKT_t = z)$ for $z \in \{Up, Down\}$ are the market state variables at time t; and $X_{i,t}$ defines the set of control variables including *Performance*, *Log(Age)*, *Log(TNA)*, *Expenses*, *Turnover*, *Load*, *Value*, *Size*, and *Momentum*. We consider specifications with and without fund fixed effects. All standard errors are clustered at both fund and time. The coefficients of interest are the loadings on the interaction terms, γ_2^z for $z \in \{Up, Down\}$.

The results, presented in Table 3, suggest a strong dependence between flow sensitivity to performance and market conditions. Flows are more sensitive to performance after up markets than after down markets: A one-standard-deviation increase in performance will lead to subsequent fund flows that are higher by about 10 percent of their standard deviation after up markets than down markets. This difference is also statistically significant based on

[2]To control for potential nonlinearity effects, we repeat the same analysis including squares of the fund-performance term. The results, which we do not report here, are unaffected.

the F-test in the lower panel of the table.

Although the behavior of fund flows may be indicative of differences in learning, it is not sufficient to judge if investors' decisions are rational. For example, even though the behavior of flows changes with market conditions (e.g., Warther (1995) and Edelen and Warner (2001)), these variations may be rational if the optimal portfolio mix for investors also depends on past market returns (e.g., Barberis (2000) and Xia (2001)). To judge the rationality of actual fund flows, we investigate the predictability of mutual fund performance and compare it to the predictions from the rational model of Berk and Green (2004).

4.2 Performance Predictability

4.2.1 Main Results

The Berk and Green (2004) model predicts that rational investors move capital across funds in an attempt to benefit from future abnormal returns offered by some funds. The resulting capital flows adjust the size of each fund such that, after considering for diseconomies of scale, predicted performance going forward is the same for all funds. Fund flows chase past performance but do not help to predict future performance. Similarly, past performance helps to predict fund flows but does not help to predict future performance. We use these predictions to assess how efficiently the marginal investor allocates capital among funds in different market conditions.

We start by looking at performance persistence. Similar to Carhart (1997), we assign funds into quintile portfolios based on their past four-factor performance. Observations are then sorted based on the market condition during that month. Next, we calculate the equally weighted cumulative performance for these fund quintiles over the subsequent three, six, nine, and twelve months, depending on the market condition when these portfolios are constructed.

Figure 2 depicts the results. The top panel is for portfolios constructed in an up market and the bottom panel is for portfolios constructed in a down market. Persistence patterns differ significantly depending on whether the portfolios were constructed after an up or a down market. After an up market, subsequent alphas are monotonically increasing in past alphas. For example, in the sorting period ($t = 0$), the spread in performance between the top and bottom-quintile funds is around 5.5%. While the spread subsequently narrows, it remains positive and economically significant, ranging from 1.0% after three months to 1.7% after twelve months. In contrast, after a down market, the sorting is not preserved. While the top-quintile funds outperform the bottom-quintile funds by 7.2% in the sorting period, subsequent alphas do not seem to be related to past alphas. Graphically, the lines in the upper panel do not intersect, while those in the bottom panel exhibit multiple crossing points.[3] The findings suggest that past performance can be used to predict future fund performance after periods of high market returns but not after periods of low market returns.

We next examine whether fund flows can be used to predict future performance and how such predictability depends on market conditions. We construct two equally weighted portfolios – the "High" portfolio includes funds with flows that are higher than the median flow in the past month and the "Low" portfolio includes funds with flows that are lower than the median flow.[4] These portfolios are held for one, three, six, and twelve months.

Let $R_{+,t+1}$ be the excess return on the portfolio of funds with above-median flows and $R_{-,t+1}$ be the excess return on the portfolio of funds with below-median flows. Also, $F_{k,t+1}$ represents the return on factor k, and $\beta_{k,j}$ is the loading on factor k, where $j \in \{+, -\}$. We begin by estimating an unconditional regression model of each portfolio's returns on the four

[3]For robustness, we repeat the same analysis with quarterly frequency or based on decile portfolios; the qualitative findings remain unchanged.

[4]This approach deviates slightly from that in Zheng (1999) and Sapp and Tiwari (2004) who sort funds based on positive and negative flows. While the approach these papers take is not as critical in the context of the unconditional framework, it is less desirable in our context given that the distribution of flows may vary systematically across market conditions. Nevertheless, the qualitative aspects of our results remain unchanged if we follow the alternative approach instead.

factors used by Carhart (1997):

$$R_{j,t+1} = \alpha_j + \sum_{k=1}^{K} \beta_{k,j} F_{k,t+1} + \epsilon_{j,t+1}, \tag{10}$$

for $j \in \{+, -\}$. Subsequently, we augment the unconditional specification with two indicator functions for lagged up and down markets. We estimate the conditional regression model:

$$R_{j,t+1} = \alpha_j^0 + \alpha_j^{Up} * I(MKT_t = Up) + \alpha_j^{Down} * I(MKT_t = Down) + \sum_{k=1}^{K} \beta_{k,j} F_{k,t+1} + \epsilon_{j,t+1}. \tag{11}$$

Table 4 presents the results. The table is divided into four sections, each corresponding to a different investment horizon. The first two columns of each section report results from unconditional regressions whereas the next two columns report results from conditional regressions. The bottom panel of the table reports two sets of results. The first two columns in each section show whether the conditional alpha is different from zero separately for up and down markets. The third column in each section shows whether the difference in alphas – unconditional and conditional – between these two portfolios is statistically different from zero.

Unconditionally, both groups of funds generate average alphas that are not statistically different from zero or from each other. The difference is statistically significant at conventional levels only for the six-month horizon. The economic magnitude of most of the differences is small. These findings are consistent with the absence of mutual fund performance persistence documented by Carhart (1997) and Sapp and Tiwari (2004), among others.

Turning to the conditional regressions, we find that the high-flow portfolio has an alpha that is indistinguishable from zero after down markets. However, the low-flow portfolio generally has negative alphas that are worse after down markets. As the bottom panel of Table 4 shows, the performance of the high-flow portfolio is significantly better than that of the low-flow portfolio only after up markets. Performance predictability is economically significant and ranges from 1.1% on an annualized basis over a three-month horizon to 1.7% on an annualized basis over a six-month horizon.

A strategy that buys funds with high past flows after periods of high market returns has a significantly better performance than a strategy that buys funds with low flows after periods of high market returns. A strategy that buys funds with high past flows after periods of low market returns does not, however, have a significantly better performance than a strategy that buys funds with low flows after periods of low market returns. The asymmetry is consistent with fund investors incorporating information more efficiently after periods of low market returns than after periods of high market returns. After periods of low market returns, the marginal investor in a low-flow fund would not benefit from switching to a high-flow fund but would benefit from switching after periods of high market returns, thereby earning a significantly higher risk-adjusted return.

Table 4 shows a difference in the factor loadings between the two portfolios. While all funds have positive and statistically significant loadings on the market and the size factors, funds with high past flows have a greater loading on the momentum factor than do funds with low past flows. Fund with low past flows generally have an insignificant loading on momentum for a horizon up to three months and positive loadings at horizons between six months and a year. Likewise, the portfolio of funds with high flows has a negative loading on the value factor. In turn, the sign of the loading is positive for the portfolio of funds with low flows.

To allow for the possibility that factor loadings may vary over time, we regress the high- and low-flow portfolio returns on the four factors interacted with the indicator functions of market conditions. The specification aims to study whether the pattern in performance predictability is robust to changes in factor loadings. The top part of Table 5 presents the regression results and the bottom part reports the differences in unconditional and conditional performance between the two portfolios.

Our main results remain unchanged. Unconditionally, there is no abnormal return from switching between low- and high-flow funds. Moreover, the high-flow portfolio generates a substantially higher alpha than the low-flow portfolio after up markets, at horizons of three to twelve months while both portfolios generate statistically indistinguishable performance from each other after down markets. Unsurprisingly, the magnitude of the spread decreases monotonically for longer investment horizons. Specifically, the return ranges from 1.3% for a one-year investment horizon to 2.5% on an annualized basis for a three-month horizon.

4.2.2 Robustness Tests

Although the reported results are suggestive of the important differences in performance predictability across market conditions, they may also be sensitive to the empirical design we utilize. Thus, we assess the sensitivity of these results. We summarize the key findings in Table 6. In Panel A, we examine performance predictability from switching between funds whose flows are higher than the 75th percentile of the flow distribution in the past month and funds whose flows are lower than the 25th percentile of the distribution. We still find performance predictability after up markets and no performance predictability after down markets. Moreover, the magnitude of the abnormal return increases and varies between 2% for a one-year investment horizon and 3.9% on an annualized basis for a three-month horizon, consistent with the idea that sorting on more extreme fund flows would generate stronger performance predictability.

In Panel B, rather than using past one-month fund flows as a sorting variable, we use the average flows over the past three months and the median flow as a cut-off value. The results, though economically less significant, are qualitatively similar. We find statistically significant predictability after up markets but not after down markets. The results are similar if we use a six-month average flow instead. In Panel C, we condition the strategy on past-month percentage flows rather than the dollar flows. Again, the results are similar qualitatively and the magnitudes are slightly larger than before.

Finally, in Panel D, we calculate abnormal returns using the three-factor model of Fama and French, that is, we exclude the momentum factor from Carhart's regression. The qualitative and the quantitative aspects of our results are similar for strategies after up markets. On the other hand, while we observe no statistically significant predictability after down markets, the economic magnitudes of the spread portfolio become slightly larger. The result is consistent with evidence by Sapp and Tiwari (2004) that momentum drives an important part of the observed unconditional predictability in mutual fund returns.

Our results indicate a significant degree of predictability in the returns of a strategy in which investors switch capital between high- and low-flow funds after periods of high market returns, and no predictability of such a strategy after periods of low market returns. While we believe that past fund flows are a natural choice for a predictive variable because they summarize the information used by investors coming from various sources, we also check if predictability persists with other predictive variables.

Another signal that investors might consider is past raw returns. In particular, Lynch and Musto (2003) document that investors' fund flows are highly sensitive to past raw returns and thus it is legitimate to believe that investors could base their decisions on such information. To this end, we use a three-month lagged fund return as a predictive variable and sort funds into a group with positive returns and a group with negative returns. We repeat the analysis presented in Table 5 using raw returns.

The results with the new predictive variable are qualitatively similar to those reported in Table 5. There is a significant degree of performance predictability after periods of high market returns but no performance predictability after periods of low market returns. Moreover, as earlier, there is little performance predictability for the very short, one-month investment horizon and strong performance predictability for the three-month, six-month, and twelve-month investment horizons. The economic magnitude of the results is comparable to that of strategies that condition on past fund flows. All the portfolio returns are significant at the 1% level.

Finally, the predictability results might rely on differences in equally weighted portfolios. In this approach, we assign a greater weight to smaller funds than the market does. To the extent that small funds systematically differ from large funds, the differences in composition of funds across different portfolios and times could produce biased results. To account for that, we repeat the analysis using value-weighted fund portfolios. The economic and statistical magnitudes of the results remain unchanged. Thus, the predictability results are unlikely to be driven by differences between small and large funds.

In summary, we find evidence suggesting that key pieces of information – raw returns, risk-adjusted returns, and fund flows – are processed differently by the marginal investor after periods of high market returns and periods of low market returns. Using the Berk and Green (2004) model to derive implications for the cross section of fund performance in the presence of fully rational fund flows, our findings suggest that capital is allocated more efficiently after periods of low market returns than after periods of high market returns. Further, the model's predictions allow us to interpret the inefficiency. It has been suggested elsewhere that boundedly rational investors may overreact to information but, we find that mutual fund investors underreact to information after periods of high market returns. Funds with low past performance and low flows tend to remain too large after periods of high market returns, which gives rise to subsequent abnormally low performance for up to a year.

5 Possible Explanations of Empirical Results

We now entertain several hypotheses that could potentially explain our findings. We first consider rational explanations related to transaction costs or mechanical patterns in the data. Subsequently, we evaluate our results from a behavioral perspective.

5.1 Transaction Costs

The asymmetric inefficiencies we report might be the result of time-varying transaction costs. In particular, transaction costs would have to offset any abnormal gain unexplained by the common factors, implying that transaction costs are significantly higher after up markets than after down markets. Although direct trading costs or fund expenses do not differ that much over time, perhaps transaction costs due to differences in investors' taxation bases may generate such time variation. For example, after up markets, investors who invest in high-flow funds may be more likely to have accrued higher taxable income than those investing in low-flow funds. As a result, the gap in their returns might simply be offset by their tax liability.

Although it is generally difficult to measure directly tax impacts on each mutual fund investor, tax liabilities are likely to be positively correlated with the degree of momentum and turnover a fund exhibited in the past. To this end, we test the tax story in two ways: Conditioning on funds' momentum loading, and conditioning on their turnover ratio. Operationally, we first sort funds according to their momentum loading: High-momentum funds are defined as those in which the *Momentum* indicator is greater than three; funds with *Momentum* below three are low-momentum funds. Subsequently, we evaluate the performance predictability of those two portfolios after up and down markets.

Panels A and B of Table 7 report the results for momentum-sorted portfolios. The results are qualitatively consistent with the previous findings for both low- and high-momentum portfolios. We find statistically significant return predictability after up markets but not after down markets. Although we find that the magnitude of the predictability is slightly larger for the high-momentum portfolio, consistent with the tax explanation, the differences between the two portfolios are generally small.

Similarly, Panels C and D of Table 7 report the results for portfolios of funds sorted by turnover ratios —above and below the sample median. We find strong performance predictability in both low- and high-turnover portfolios after up markets and no performance predicability after down markets. The economic magnitude is slightly larger for the high-turnover portfolio, but once again the difference between the two portfolios is economically negligible.

We conclude that our results are unlikely to be entirely driven by differences in transaction costs induced by capital gains taxation.

5.2 Style-Based Predictability

Another possible explanation for our results is that the predictability patterns we observe are an artifact of a particular correlation structure between the returns on our switching strategy and those on a well-known passive strategy. For example, if high-flow funds were value funds and low-flow funds were growth funds, switching between the two types of funds would be equivalent to following a value strategy. To the extent that the profitability of the value strategy were high in up markets and zero in down markets, we would obtain observationally equivalent results. Although our empirical approach controls for any systematic differences in factor exposure, one might argue that the adjustment may be imprecise. Hence, we examine the predictability results within different investment styles. Table 8 reports the results.

In Panels A and B, we split funds into broad classes of value and growth funds. Value funds are defined as those in which the *Value* indicator is greater than three; funds with *Value* indicator below three are growth funds. We find qualitatively similar patterns within both classes of funds. The magnitude of the observed predictability is slightly stronger for value funds for shorter horizons and stronger for growth funds at longer horizons. In Panels C and D, we compare smaller-cap and larger-cap funds. Smaller-cap funds are defined as those in which the *Size* indicator is below three; the funds with *Size* indicator above three are larger-cap funds. We find no significant difference in economic magnitudes between the two categories of funds. However, the statistical significance is much stronger for larger-cap funds. This difference is possibly due to the fact that our sample is tilted towards larger-cap funds, which may help the precision of our estimates.

We conclude that our results are unlikely to be due to investors trading based on well-known passive investment strategies.

5.3 Survivorship Bias

The design of our performance predictability tests relies on the fact that the mutual funds included in each portfolio are present in the sample throughout the entire evaluation period of up to twelve months. Our tests could be biased if some funds dropped out of the sample before the end of the evaluation period. This would produce a survivorship bias (Brown et al. (1992); Carpenter and Lynch (1999)). The survivorship bias issue would not be important if the attrition process randomly affected both portfolios. In such a case, any performance difference would be offset by the difference in the long-short portfolio. On the other hand, our results could result from the survivorship bias if for example funds in high-flow portfolio were subject to more attrition, and thus had better average performance, than funds in low-flow portfolio, especially after up markets.

We evaluate such a possibility by explicitly looking at the survival rates of different portfolios while also conditioning on market returns. In addition, we calculate survival rates separately for each investment horizon. Table 9 reports the results. As expected, we find that the survival rates decrease with an increase in investment horizon. Nevertheless, the average survival rates are generally quite high: In the portfolio with a one-year investment horizon these rates approach 90%. Moreover, we find no evidence of significant differences in survivorship across the different conditional portfolios. If anything, the difference in survival rates is slightly higher for portfolios after down markets. Hence, we conclude that the asymmetric predictability in performance we identify is unlikely to be driven by differences in funds' survivorship.

5.4 Investors' Capital Allocation Mistakes

In this section, we explore a behavioral explanation for our findings. We argue that the mechanism behind our findings could be that the marginal investor simply makes more mistakes when allocating capital after periods of high market returns than after periods of low market returns. In particular, our results suggest that the marginal investor in mutual funds appears to leave too much capital in poorly performing funds and not move enough capital into well performing funds after periods of high market returns.

Our starting point for testing this hypothesis is that retail investors are more likely to make capital allocation mistakes than are institutional investors. Specifically, Lamont and Thaler (2003) and Brunnermeier and Nagel (2004) provide empirical evidence of irrational investment decisions by individual or retail investors. Consequently, if capital allocation mistakes are driving our findings of asymmetric predictability in mutual fund performance, we expect the observed differences in flow-performance sensitivity and in fund predictability to be more pronounced for retail investors than for institutional investors.

To test these predictions formally, we divide funds into retail and institutional categories using the ex-ante classification provided in the Mutual Fund CRSP Database and in the case of missing observations using hand-collected data from fund prospectuses. We then begin our analysis by estimating a multivariate regression model in which we test whether the sensitivity of flows to performance varies between two groups of funds. Specifically, we estimate the specification used in equation (9) separately for the two groups of funds.

Table 10 shows that retail fund flows are much more sensitive to past performance after up markets than after down markets. The difference between the two sensitivities, evaluated using an F-test, is statistically significant at the 1% level. At the same time, we find that the difference in sensitivities across market conditions is statistically insignificant for institutional flows. This result suggests that the time variation in flows is driven by changes in the behavior of unsophisticated fund investors rather than in the behavior of sophisticated ones.

We further test whether this differential responsiveness in flows drives the observed differences in performance predictability across market conditions. To do so, we estimate equation (11) separately for retail and institutional investors. Panel A of Table 11 presents the results for retail investors. We observe patterns similar to those presented in Table 5, i.e., strong predictability in the performance earned by switching capital across funds after up markets but no predictability in performance after down markets. The magnitude of the results is economically significant and varies from 1.8% for a one-year horizon to 3.2% on an annualized basis for a three-month horizon. In Panel B, we present the results for institutional investors. We find no predictability in the performance earned from switching across funds after up or down markets.

Another way in which we can evaluate the behavioral hypothesis is based on the argument that young funds are generally regarded as new and fashionable and thus may attract flows from less sophisticated investors. Simultaneously, these funds are also less known to investors, which makes it more likely for investors to make mistakes in their investments. To this end, we consider two groups of funds: Funds that are not more than three years old, and funds that are nine or more years old, which is the median fund age in our sample. For each group, we again consider predictability patterns in the model in which investors can switch across different types of funds. Table 12 reports the results.

We find significant degree of performance predictability in both groups of funds after up markets but not after down markets. However, the magnitude of the observed abnormal returns is quite different between the two groups. The results are very significant for young funds, especially for short-term, one-month and three-month, horizons and are less significant for longer horizons. In turn, the results for older funds are significant only for middle-term horizons. These findings are consistent with the explanation that less sophisticated investors channel their funds extensively and quickly to new mutual funds and are more subject to repeat the same capital allocation mistakes over time.

The results in this section suggest that the primary factor for the observed differences in predictability across market conditions could be that the marginal dollar invested in funds is less rational after up markets than it is after down markets. On the other hand, it is less likely that the results can be explained by other rational stories based on differences in transaction costs, style, or survivorship.

6 Predictability in Fund Managers' Strategies

In light of the evidence that mutual fund investors incorporate information efficiently after periods of low market returns but inefficiently after periods of high market returns, we investigate whether fund managers respond differentially to market conditions. Following high market returns, when the marginal fund investor does not seem to allocate capital across funds rationally, fund managers should have weaker incentives to exert costly effort to acquire unique information. In contrast, their incentives should strengthen when the mutual fund industry is more efficient, that is, after periods of low market returns. Thus, the type of information collected, processed, and used by mutual fund managers to form portfolios should vary with market conditions.

One way in which such time variation in incentives may show up is that when more unique information is known, funds should pursue investment strategies that are cross-sectionally more distinct. Consequently, we examine how the level of cross-sectional dispersion in investment strategies moves with market conditions. We use measures similar to those of Chevalier and Ellison (1999) to capture dispersion in managers' portfolios with respect to a typical fund portfolio at time t.

We consider three dispersion measures. The first measure is *Beta Deviation*. It measures boldness in the sense of taking a large bet on the direction of the market. The variable is calculated as the absolute value of the difference between a fund i's beta in month t and the average beta in that month across all funds in the fund's objective class. Individual fund beta is a market beta from a four-factor model calculated using 36 months of past returns:

$$BetaDeviation_{i,t} =\mid Beta_{i,t} - \overline{Beta}_{g,v} \mid . \tag{12}$$

The second measure is *Sector Deviation*, which measures boldness in the style of a manager. The measure captures how much a manager concentrates her portfolio in sectors that differ from those that are most popular at the time. Specifically, *Sector Deviation* is defined as the mean square root of the sum of squared differences between the share of fund *i*'s assets in each of 10 industry sectors of Fama and French (1997) and the mean share in each sector in quarter t among all funds in fund *i*'s objective class: aggressive growth, growth, or value.[5]

$$SectorDeviation_{i,t} = \frac{1}{J}(\sum_{j} \sqrt{\sum_{k} (w_{kj} - \overline{w}_{g,v})^2}), \tag{13}$$

where w_k is the weight of stock k in industry j, and $\overline{w}_{g,v}$ is the weight of a fund objective (growth, value) in the same industry j; J is the number of distinct industries.

The third dispersion measure is *Unsystematic Deviation* which measures fund boldness in terms of a departure from a typical portfolio, based on the level of its unsystematic risk. Specifically, the variable is calculated as the absolute value of the difference between a fund's unsystematic risk, *Unsystematic Risk*, and the sample average of this variable over all funds in fund *i*'s objective class in month t. *Unsystematic Risk* is the absolute value of the residual from the four-factor model of Carhart (1997):

$$UnsystematicDeviation_{i,t} =\mid UnsystematicRisk_{i,t} - \overline{UnsystematicRisk}_{g,v} \mid . \tag{14}$$

By construction, a smaller value for each of these variables corresponds to less dispersion in the managers' portfolios and thus possibly less unique information being acquired.

[5] To identify investment objectives we use CDA style categories 2, 3, and 4. Industry sectors are defined using a modified 10-industry classification of Fama and French, as in Kacperczyk, Sialm, and Zheng (2005).

We relate the measures of dispersion of investment strategies to market conditions by estimating the regression model:

$$Dispersion_{i,t} = \lambda_0 + \lambda_1 I(MKT_t = Up) + \lambda_2 I(MKT_t = Down) + \lambda_3 X_{i,t} + FundF.E. + \epsilon_{i,t}. \tag{15}$$

Here, *Dispersion* denotes the degree of similarity in investment strategy of fund i at time t and it is proxied by *Beta Deviation*, *Sector Deviation*, and *Unsystematic Deviation*. $I(MKT_t = Up)$ and $I(MKT_t = Down)$ represent the state of the market, and X defines the set of control variables. Our controls include $Performance$, $Log(Age)$, $Log(TNA)$, $Expenses$, $Turnover$, $Flow$, $Value$, $Size$, and $Momentum$. In addition, some specifications include fund fixed effects.

The coefficients of interest are λ_1 and λ_2. We expect these coefficients to vary systematically if the fund strategies differ after up and down markets. For instance, if the fund managers' strategies are similar after up but different after down markets, λ_1 will be negative and λ_2 will be positive.

The results, presented in Table 13, show that the managerial strategies are generally more dispersed after down markets than after up markets. The difference between up markets and down markets is statistically significant for measures of *Beta Deviation* and *Unsystematic Deviation* and is statistically insignificant for *Sector Deviation*. The results hold even when we include fund fixed effects. Moreover, the coefficient on $I(MKT_t = Up)$ is negative and the coefficient on $I(MKT_t = Down)$ is positive for two out of the three measures of dispersion. Overall, our findings are consistent with the hypothesis that fund managers internalize the behavior of fund investors in their trading strategies.

7 Conclusion

Using a rational equilibrium model of mutual funds as a benchmark, we document that the marginal investor in the mutual fund sector does not appear to always behave rationally: She appears to be more rational after periods of low market returns than after periods of high market returns.

A number of findings lead to our conclusion. First, we observe a significant degree of performance persistence after periods of high market returns and no persistence after periods of low market returns. Second, we find a significant degree of cross-sectional predictability in abnormal returns. In particular, investing in a strategy that takes a long position in funds with high flows would have earned an abnormal return that is economically and statistically larger than a similar strategy using funds with low flows after periods of high market returns and approximately the same abnormal return after periods of low market returns. Likewise, investing in a strategy that takes a long position in funds with high returns, either raw or risk adjusted, would have earned an abnormal return that is economically and statistically larger than that of a similar strategy using funds with low returns after periods of high market returns and approximately the same abnormal return after periods of low market returns. This predictability is mostly pronounced for investment horizons between three and twelve months and is robust to the inclusion of standard risk and style controls, as well as the time-series variation in factor loadings.

Using the argument that irrational behavior is more likely to come from retail investors than institutional ones, we document that the differential response in fund flows across market conditions is largely confined to flows into retail funds rather than those into institutional funds, suggesting that the observed differences in returns result from differences in the behavior of retail investors. Consistent with an equilibrium in which fund managers optimally adjust their incentives to the efficiency level of fund flows, we find that fund managers' investment strategies are more dispersed cross-sectionally after periods of low market returns than after periods of high market returns.

Overall, our results imply that the equity mutual fund industry is less informationally efficient after high market returns, when the industry size increases, than after low market returns. This finding, in turn, has strong implications for the overall market efficiency debate and asset prices in general. Indeed, recent work by Vayanos and Woolley (2008) examines implications of institutional trading for asset prices. Studying the implications of our findings in such a setting is a fruitful area for future research.

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Appendix A. Sample Selection

We base our selection criteria on the objective codes and on the disclosed asset compositions. First, we select funds with the following ICDI objectives: AG, GI, LG, or IN. If a fund does not have any of the above ICDI objectives, we select funds with the following Strategic Insight objectives: AGG, GMC, GRI, GRO, ING, or SCG. If a fund has neither the Strategic Insight nor the ICDI objective, then we go to the Wiesenberger Fund Type Code and pick funds with the following objectives: G, G-I, AGG, GCI, GRI, GRO, LTG, MCG, and SCG. If none of these objectives are available and the fund has the CS policy (Common Stocks are the mainly held securities by the fund), then the fund will be included. We exclude funds that have the following Investment Objective Codes in the Spectrum Database: International, Municipal Bonds, Bond and Preferred, and Balanced. Since the reported objectives do not always indicate whether a fund portfolio is balanced or not, we also exclude funds that, on average, hold less than 80% in stocks.

Elton, Gruber, and Blake (2001) identify a form of survival bias in the CRSP mutual fund database, which results from a strategy used by fund families to enhance their return histories. Fund families might incubate several private funds and they will only make public the track record of the surviving incubated funds, while the returns for those funds that are terminated are not made public. To address this incubation bias, we exclude the observations where the year for the observation is prior to the reported fund starting year and we exclude observations where the names of the funds are missing in the CRSP database. Incubated funds also tend to be smaller, which motivates us to exclude funds that had in the previous month less than $5 million in assets under management.

In the next step, we are able to match about 94% of the CRSP funds to the Spectrum database. The unmatched funds tend to be younger and smaller than the funds for which we find data in Spectrum. Wermers (2000) mentions that the Spectrum data set often does not have any holdings data available during the first few quarters listed in the CRSP database.

Mutual fund families introduced different share classes in the 1990s. Since different share classes have the same holdings composition, we aggregate all the observations pertaining to different share classes into one observation. For the qualitative attributes of funds (e.g., name, objectives, year of origination), we retain the observation of the oldest fund. For the total net assets under management (TNA), we sum the TNAs of the different share classes. Finally, for the other quantitative attributes of funds (e.g., returns, expenses, loads), we take the weighted average of the attributes of the individual share classes, where the weights are the lagged TNAs of the individual share classes.

For most of our sample period, mutual funds are required to disclose their holdings semi-annually. A large number of funds disclose their holdings quarterly, while a small number of funds have gaps between holding disclosure dates of more than six months. To fill these gaps, we impute the holdings of missing quarters using the most recently available holdings, assuming that mutual funds follow a buy-and-hold strategy. In our sample, 72% of the observations are from the most recent quarter and less than 5% of the holdings are more than two quarters old. We exclude funds that have fewer than 10 identified stock positions and funds that did not disclose their holdings during the last year. This final selection criterion reduces the number of mutual funds used in this study to 3,261 funds.

Table 1: **Market Conditions**

This table presents means, standard deviations, and transition probabilities for different market conditions. $I(MKT_t = Up)$ equals one when the three-month moving average of market excess return is higher than the 75th percentile of the historical three-month moving average of market returns (starting Q3 of 1926); and zero otherwise. $I(MKT_t = Mid)$ equals one when the three-month moving average of market excess return is between the 25th and 75th percentiles of the historical three-month moving average of market returns (starting Q3 of 1926); and zero otherwise. $I(MKT_t = Down)$ equals one when the three-month moving average of market excess return is lower than the 25th percentile of the historical three-month moving average of market returns (starting Q3 of 1926); and zero otherwise. The sample covers the period 1980-2005.

Conditions	**N**	**MKT Return**		**Conditional Probability**		
		Mean	S.D.	$I(MKT_{t+1} = Up)$	$I(MKT_{t+1} = Mid)$	$I(MKT_{t+1} = Down)$
$I(MKT_t = Up)$	39	0.048	0.030	0.526	0.474	0.000
$I(MKT_t = Mid)$	232	0.012	0.035	0.084	0.836	0.080
$I(MKT_t = Down)$	38	-0.030	0.065	0.000	0.526	0.474

Table 2: **Summary Statistics**

Summary statistics are for all market conditions (Panel A), and conditional on either up- (Panel B) or down market (Panel C). *Flow* is defined as $Flow = \frac{TNA_t - TNA_{t-1} * (1+R_t)}{TNA_{t-1}}$. R is the net return of the fund portfolio. *Performance* is the alpha (including residual) from the four-factor model of excess fund returns projected on market premium, size, value, and momentum factors. *Age* is the fund age. *TNA* is the total net assets of a fund (in Millions). *Expenses* is the fund expense ratio. *Turnover* is fund turnover. *Load* is the total fund load. *Value* is the average score of all stocks in the fund portfolio, where each stock is assigned a score (from 1 to 5) based on its book-to-market ratio. *Size* is the average score of all stocks in the fund portfolio, where each stock is assigned a score (from 1 to 5) based on its market capitalization. *Momentum* is the average score of all stocks in the fund portfolio, where each stock is assigned a score (from 1 to 5) based on its past 12-month returns. *BetaDeviation* is the absolute value of the difference between a fund's beta in month t and the average beta in that quarter of all funds in the fund's objective class. Individual fund beta is a market beta from a four-factor model calculated using 36 months of past returns. *SectorDeviation* is the mean square root of the sum of squared differences between the share of a fund's assets in each of ten industry sectors of Fama and French (1997) and the mean share in each sector in month t among all funds in the fund's objective class (aggressive growth, growth, or value). *UnsystematicDeviation* is the absolute value of the difference between a fund's unsystematic risk, *UnsystematicRisk*, and the sample average of this variable over all funds in the fund's objective class in month t. *UnsystematicRisk* is the absolute value of the residual from the four-factor model of Carhart (1997). $I(MKT_t = Up)$ equals one when the three-month moving average of market excess return is higher than the 75th percentile of the historical three-month moving average of market returns (starting Q3 of 1926); and zero otherwise. $I(MKT_t = Down)$ equals one when the three-month moving average of market excess return is lower than the 25th percentile of the historical three-month moving average of market returns (starting Q3 of 1926); and zero otherwise. The data cover all equity mutual funds for the period 1980 to 2005.

	Panel A: All Market Conditions				
	Mean	**S.D.**	**Median**	**p25**	**p75**
Flow	0.0123	0.2381	-0.0003	-0.0147	0.0198
Return	0.0088	0.0549	0.0112	-0.0209	0.0406
Performance	-0.0012	0.0225	-0.0012	-0.0112	0.0087
Age	13.9	14.2	9.0	5.0	17.0
TNA	920.6	3,636.5	153.8	44.9	543.5
Expenses	0.0129	0.0048	0.0123	0.0097	0.0154
Turnover	92.51	132.33	67.00	35.20	115.00
Load	0.0222	0.0261	0.0051	0.0000	0.0475
Value	2.6	0.5	2.6	2.2	2.9
Size	4.1	1.0	4.4	3.5	4.8
Momentum	3.3	0.6	3.3	2.9	3.7
Beta Deviation	0.1428	0.2767	0.1062	0.0505	0.1846
Sector Deviation	0.1875	0.0922	0.1703	0.1265	0.2280
Unsystematic Deviation	0.0084	0.0094	0.0066	0.0033	0.0106

	Panel B: $I(MKT_t = Up)$				
	Mean	**S.D.**	**Median**	**p25**	**p75**
Flow	0.0147	0.3008	-0.0016	-0.0208	0.0208
Return	0.0474	0.0419	0.0435	0.0183	0.0674
Performance	-0.0025	0.0224	-0.0023	-0.0137	0.0085
Age	14.5	14.5	9.0	5.0	18.0
TNA	884.8	3,457.0	150.8	44.9	529.0
Expenses	0.0126	0.0048	0.0120	0.0095	0.0150
Turnover	92.61	137.04	67.00	35.93	114.21
Load	0.0230	0.0280	0.0022	0.0000	0.0475
Value	2.6	0.5	2.6	2.2	3.0
Size	4.0	1.0	4.4	3.4	4.8
Momentum	3.3	0.6	3.2	2.9	3.7
Beta Deviation	0.1435	0.3822	0.1042	0.0503	0.1795
Sector Deviation	0.1916	0.0900	0.1758	0.1309	0.2334
Unsystematic Deviation	0.0086	0.0083	0.0070	0.0035	0.0109

	Panel C: $I(MKT_t = Down)$				
	Mean	**S.D.**	**Median**	**p25**	**p75**
Flow	0.0073	0.3897	-0.0025	-0.0163	0.0158
Return	-0.0289	0.0790	-0.0268	-0.0782	0.0200
Performance	-0.0001	0.0296	-0.0002	-0.0139	0.0142
Age	13.4	13.8	8.0	5.0	16.0
TNA	978.1	3,720.3	155.9	43.3	558.9
Expenses	0.0129	0.0047	0.0124	0.0099	0.0155
Turnover	98.65	132.08	72.00	39.00	122.00
Load	0.0212	0.0254	0.0041	0.0000	0.0458
Value	2.5	0.5	2.5	2.2	2.9
Size	4.2	0.9	4.6	3.6	4.9
Momentum	3.3	0.7	3.3	2.8	3.8
Beta Deviation	0.1446	0.1518	0.1102	0.0522	0.1924
Sector Deviation	0.1855	0.0913	0.1686	0.1230	0.2279
Unsystematic Deviation	0.0105	0.0106	0.0083	0.0042	0.0134

Table 3: **Flow-Performance Relationship Conditional on Market Returns**

The dependent variable is fund flow ($Flow$). Bottom row provides the F-test along with its p-values of the differences between coefficients on $I(MKT_t = Up)$ and $I(MKT_t = Down)$. Our controls include Performance, Log(Age), Log(TNA), Expenses, Flow, Turnover, Value, Size, and Momentum. Flow, Performance, and Turnover have been winsorized at the 1% level. All variables are defined in Table 2. $I(MKT_t = Up)$ equals one when the three-month moving average of market excess return is higher than the 75th percentile of the historical three-month moving average of market returns (starting Q3 of 1926); and zero otherwise. $I(MKT_t = Down)$ equals one when the three-month moving average of market excess return is lower than the 25th percentile of the historical three-month moving average of market returns (starting Q3 of 1926); and zero otherwise. Standard errors (in parentheses) are clustered by fund and time. A bottom panel reports an F-test of differences in coefficients on $I(MKT_t = Up)$ and $I(MKT_t = Down)$ along with their p-values (in parentheses). The data cover the period 1980 to 2005.

	Flow	
Performance	0.237	0.184
	(0.027)	(0.024)
Log(Age)	-0.007	-0.014
	(0.001)	(0.002)
Log(TNA)	0.001	-0.002
	(0.0004)	(0.001)
Expenses	-0.024	0.224
	(0.140)	(0.219)
Turnover	-0.001	0.001
	(0.001)	(0.000)
Load	0.024	-0.024
	(0.019)	(0.033)
Value	0.005	0.001
	(0.001)	(0.013)
Size	-0.001	-0.001
	(0.001)	(0.001)
Momentum	0.006	0.009
	(0.001)	(0.001)
$I(MKT_t = Up)$	0.076	0.085
x Performance	(0.091)	(0.086)
$I(MKT_t = Down)$	-0.160	-0.132
x Performance	(0.058)	(0.056)
$I(MKT_t = Up)$	0.007	0.007
	(0.005)	(0.004)
$I(MKT_t = Down)$	-0.011	-0.011
	(0.004)	(0.004)
Constant	-0.013	0.025
	(0.002)	(0.012)
Observations	191,721	191,721
R^2	0.02	0.10
Fund fixed effects	No	Yes

F-test: $I(MKT_t = Up) \times Perf. = I(MKT_t = Down) \times Perf.$		
Difference	0.236	0.217
p-value	(0.000)	(0.026)

Table 4: **Flow-Based Portfolios with Unconditional Risk Loadings**

Each month we construct portfolios of funds based on their past dollar flows. *High* denotes the return on the equally weighted portfolio of funds which received flows that are higher than the median flow in a given period; *Low* is the return on the equally weighted portfolio of funds which received flows that are lower than the median flow in a given period. Both returns are regressed on a set of four factors: market premium (MKTPREM), size (SMB), value (HML), and momentum (UMD), and two indicator functions. $I(MKT_t = Up)$ equals one when the three-month moving average of market excess return is higher than the 75th percentile of the historical three-month moving average of market returns (starting Q3 of 1926); and zero otherwise. $I(MKT_t = Down)$ equals one when the three-month moving average of market excess return is lower than the 25th percentile of the historical three-month moving average of market returns (starting Q3 of 1926); and zero otherwise. Columns (1)-(4) consider monthly returns one month ahead, columns (5)-(8) monthly returns three months ahead, columns (9)-(12) monthly returns six months ahead, and columns (13)-(16) monthly returns 12 months ahead. Standard errors (in parentheses) are adjusted for autocorrelation up to 12 lags using the procedure as in Newey and West (1987). A bottom panel reports monthly returns along with their p-values (in parentheses) on portfolios which condition on both market conditions and fund flows. The panel also reports the results of the F-test of the differences between the respective portfolios. The data covers the period 1980 to 2005.

	1 Month				**3 Months**				**6 Months**				**12 Months**			
$Flow_{t-1}$	High	Low	High	Low	High	Low	High	Low	High	Low	High	Low	High	Low	High	Low
MKTPREM	0.970	0.976	0.988	0.982	0.943	0.980	0.966	0.994	0.952	0.975	0.963	0.983	0.951	0.947	0.962	0.951
	(0.015)	(0.017)	(0.013)	(0.016)	(0.024)	(0.017)	(0.015)	(0.016)	(0.022)	(0.021)	(0.018)	(0.020)	(0.024)	(0.036)	(0.023)	(0.034)
SMB	0.237	0.12	0.222	0.122	0.253	0.126	0.239	0.130	0.223	0.171	0.237	0.181	0.241	0.170	0.261	0.181
	(0.021)	(0.042)	(0.016)	(0.046)	(0.019)	(0.052)	(0.016)	(0.053)	(0.021)	(0.035)	(0.020)	(0.033)	(0.032)	(0.043)	(0.030)	(0.040)
HML	-0.007	0.034	-0.022	0.014	-0.026	0.036	-0.040	0.025	-0.043	0.063	-0.043	0.050	-0.036	0.065	-0.040	0.048
	(0.031)	(0.046)	(0.033)	(0.053)	(0.024)	(0.044)	(0.025)	(0.049)	(0.026)	(0.045)	(0.026)	(0.049)	(0.019)	(0.057)	(0.024)	(0.061)
UMD	0.043	-0.016	0.041	-0.014	0.029	-0.027	0.023	-0.033	0.032	0.004	0.042	0.003	0.055	0.044	0.078	0.037
	(0.019)	(0.022)	(0.015)	(0.026)	(0.016)	(0.024)	(0.010)	(0.026)	(0.019)	(0.018)	(0.011)	(0.017)	(0.024)	(0.029)	(0.021)	(0.027)
$I(MKT_t = Up)$			-0.001	0.001			-0.001	-0.001			-0.000	-0.001			0.000	-0.001
			(0.001)	(0.001)			(0.001)	(0.001)			(0.000)	(0.001)			(0.000)	(0.000)
$I(MKT_t = Down)$			0.000	-0.001			0.001	-0.001			0.000	-0.000			-0.000	-0.000
			(0.001)	(0.002)			(0.001)	(0.001)			(0.000)	(0.001)			(0.000)	(0.000)
Constant	-0.001	-0.001	-0.001	-0.001	-0.000	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	307	307	307	307	305	305	305	305	302	302	302	302	296	296	296	296
R^2	0.97	0.96	0.97	0.96	0.97	0.96	0.97	0.96	0.97	0.96	0.97	0.96	0.97	0.95	0.97	0.95

	1 Month			**3 Months**			**6 Months**			**12 Months**		
$Flow_{t-1}$	High	Low	High-Low	High	Low	High-Low	High	Low	High-Low	High	Low	High-Low
Unconditional (in %)	-0.058	-0.082	0.024	-0.039	-0.103	0.064	-0.062	-0.132	0.070	-0.081	-0.132	0.051
	(0.273)	(0.225)	(0.696)	(0.404)	(0.048)	(0.148)	(0.154)	(0.063)	(0.034)	(0.047)	(0.002)	(0.172)
$I(MKT_t = Up)$ (in %)	-0.173	-0.028	-0.145	-0.104	-0.196	0.092	-0.103	-0.241	0.138	-0.116	-0.213	0.097
	(0.066)	(0.852)	(0.239)	(0.041)	(0.031)	(0.051)	(0.043)	(0.000)	(0.005)	(0.009)	(0.000)	(0.020)
$I(MKT_t = Down)$ (in %)	-0.039	-0.161	0.122	-0.066	-0.130	0.076	-0.060	-0.130	0.070	-0.135	-0.134	-0.001
	(0.669)	(0.224)	(0.330)	(0.347)	(0.042)	(0.284)	(0.393)	(0.064)	(0.169)	(0.006)	(0.043)	(0.981)

Table 5: **Performance of Flow-Based Portfolios with Conditional Risk Loadings**

Each month we construct portfolios of funds based on their dollar flows. *High* denotes the return on the equally weighted portfolio of funds which received flows that are higher than the median flow in a given period; *Low* is the return on the equally weighted portfolio of funds which received flows that are lower than the median flow in a given period. Both returns are regressed on a set of four factors: market premium (MKTPREM), size (SMB), value (HML), and momentum (UMD), and their interactions with two indicator functions: $I(MKT_t = Up)$ equals one when the three-month moving average of market excess return is higher than the 75th percentile of the historical three-month moving average of market returns (starting Q3 of 1926); and zero otherwise. $I(MKT_t = Down)$ equals one when the three-month moving average of market excess return is lower than the 25th percentile of the historical three-month moving average of market returns (starting Q3 of 1926); and zero otherwise. Columns (1)-(2) consider monthly returns one month ahead, columns (3)-(4) monthly returns three months ahead, columns (5)-(6) monthly returns six months ahead, and columns (7)-(8) monthly returns twelve months ahead. Standard errors (in parentheses) are adjusted for autocorrelation up to 12 lags using the procedure as in Newey and West (1987). A bottom panel reports monthly returns along with their p-values (in parentheses) on portfolios which condition on both market conditions and fund flows. The panel also reports the results of the F-test of the differences between the respective portfolios. The data cover the period 1980 to 2005.

	1 Month		**3 Months**		**6 Months**		**12 Months**	
$Flow_{t-1}$	High	Low	High	Low	High	Low	High	Low
MKTPREM	0.979	0.986	0.968	0.990	0.963	0.972	0.958	0.935
	(0.011)	(0.016)	(0.013)	(0.017)	(0.017)	(0.023)	(0.023)	(0.038)
SMB	0.231	0.108	0.234	0.122	0.228	0.186	0.268	0.187
	(0.016)	(0.048)	(0.020)	(0.054)	(0.024)	(0.035)	(0.033)	[0.044)
HML	-0.049	-0.009	-0.055	0.021	-0.057	0.036	-0.055	0.045
	[-0.024)	(-0.047)	(-0.023)	(0.052)	(-0.024)	(0.047)	(-0.025)	(0.064)
UMD	0.022	-0.039	0.020	-0.061	0.037	-0.012	0.074	0.030
	(0.012)	(-0.029)	(0.010)	(-0.031)	(0.014)	(-0.020)	(0.020)	(0.027)
MKTPREM x	-0.056	-0.021	-0.047	-0.028	-0.090	-0.036	-0.009	0.025
$I(MKT_t = Up)$	(-0.032)	(-0.038)	(-0.028)	(-0.021)	(-0.044)	(-0.031)	(-0.030)	(0.040)
MKTPREM x	0.069	-0.011	0.054	0.019	0.073	0.104	0.045	0.107
$I(MKT_t = Down)$	(0.025]	(-0.037)	(0.022)	(0.030)	(0.028)	(0.040)	(0.023)	(0.044)
SMB x	-0.063	0.074	0.017	0.120	0.080	0.063	0.000	0.029
$I(MKT_t = Up)$	(-0.042)	(0.052)	(0.042)	(0.050)	(0.046)	(0.039)	(0.036)	(0.041)
SMB x	-0.027	0.042	-0.003	-0.029	-0.004	-0.134	-0.042	-0.100
$I(MKT_t = Down)$	(-0.032)	(0.054)	(-0.044)	(-0.052)	(-0.052)	(-0.056)	(-0.046)	(-0.064)
HML x	-0.084	-0.103	-0.015	-0.079	-0.090	-0.147	0.073	0.006
$I(MKT_t = Up)$	(-0.066)	(-0.080)	(-0.028)	(-0.061)	(-0.044)	(-0.058)	(0.048)	(0.071)
HML x	0.109	0.099	0.097	0.076	0.117	0.154	0.043	0.088
$I(MKT_t = Down)$	(0.032)	(0.056)	(0.033)	(0.041)	(0.034)	(0.037)	(0.044)	(0.060)
UMD x	-0.019	0.027	-0.031	0.084	-0.060	-0.011	0.006	0.073
$I(MKT_t = Up)$	(-0.068)	(0.058)	(-0.045)	(0.036)	(-0.023)	(-0.022)	(0.066)	(0.105)
UMD x	0.053	0.047	0.044	0.050	0.045	0.035	0.025	-0.001
$I(MKT_t = Down)$	(-0.027)	(0.031)	(0.021)	(0.026)	(0.041)	(0.038)	(0.029)	(-0.029)
$I(MKT_t = Up)$	0.000	-0.001	0.000	-0.002	0.001	-0.001	0.000	-0.002
	(0.002)	(-0.002)	(0.001)	(-0.001)	(0.000)	(-0.001)	(0.001)	(-0.001)
$I(MKT_t = Down)$	-0.001	-0.001	0.000	-0.001	-0.001	-0.001	-0.001	-0.001
	(-0.001)	(-0.001)	(0.001)	(-0.001)	(-0.000)	(-0.001)	(-0.000)	(-0.001)
Constant	0.000	0.000	0.000	0.000	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.000)	(0.001)	(-0.000)	(-0.001)	(-0.000)	(-0.001)
Observations	307	307	305	305	302	302	296	296
R^2	0.97	0.97	0.97	0.96	0.97	0.97	0.97	0.95

	1 Month			**3 Months**			**6 Months**			**12 Months**		
$Flow_{t-1}$	High	Low	High-Low	High	Low	High-Low	High	Low	High-Low	High	Low	High-Low
Unconditional (in %)	-0.033	-0.071	0.038	-0.044	-0.086	0.042	-0.067	-0.103	0.036	-0.117	-0.123	0.006
	(0.354)	(0.188)	(0.446)	(0.214)	(0.093)	(0.219)	(0.092)	(0.019)	(0.150)	(0.001)	(0.004)	(0.785)
$I(MKT_t = Up)$ (in %)	-0.024	-0.148	0.124	-0.058	-0.264	0.206	0.018	-0.141	0.159	-0.142	-0.247	0.105
	(0.880)	(0.375)	(0.404)	(0.339)	(0.000)	(0.014)	(0.689)	(0.003)	(0.010)	(0.003)	(0.001)	(0.059)
$I(MKT_t = Down)$ (in %)	-0.140	-0.146	0.006	-0.058	-0.128	0.070	-0.156	-0.179	0.023	-0.156	-0.156	0.000
	(0.019)	(0.206)	(0.960)	(0.359)	(0.000)	(0.398)	(0.000)	(0.000)	(0.705)	(0.000)	(0.010)	(0.997)

Table 6: **Performance of Flow-Based Portfolios: Robustness**

Each month we construct portfolios of funds based on their dollar flows. *High* denotes the return on the equally weighted portfolio of funds which received flows that are higher than the median flow in a given period; *Low* is the return on the equally weighted portfolio of funds which received flows that are lower than the median flow in a given period. Both returns are regressed on a set of four factors: market premium (MKTPREM), size (SMB), value (HML), and momentum (UMD), and their interactions with two indicator functions: $I(MKT_t = Up)$ equals one when the three-month moving average of market excess return is higher than the 75th percentile of the historical three-month moving average of market excess returns (starting Q3 of 1926); and zero otherwise. $I(MKT_t = Down)$ equals one when the three-month moving average of market excess return is lower than the 25th percentile of the historical three-month moving average of market returns (starting Q3 of 1926); and zero otherwise. Columns (1)-(2) consider monthly returns one month ahead, columns (3)-(4) monthly returns three months ahead, columns (5)-(6) monthly returns six months ahead, and columns (7)-(8) monthly returns twelve months ahead. Standard errors (in parentheses) are adjusted for autocorrelation up to 12 lags using the procedure as in Newey and West (1987). A bottom panel reports monthly returns along with their p-values (in parentheses) on portfolios which condition on both market conditions and fund flows. The data cover the period 1980 to 2005.

Panel A: Different Cut-Off Values

	1 Month			**3 Months**			**6 Months**			**12 Months**		
$Flow_{t-1}$	High	Low	High-Low	High	Low	High-Low	High	Low	High-Low	High	Low	High-Low
$I(MKT_t = Up)$ (in %)	0.030	-0.230	0.260	0.043	-0.280	0.323	0.052	-0.151	0.203	-0.069	-0.236	0.167
	(0.840)	(0.213)	(0.233)	(0.636)	(0.000)	(0.009)	(0.220)	(0.005)	(0.025)	(0.077)	(0.005)	(0.043)
$I(MKT_t = Down)$ (in %)	-0.149	-0.169	0.020	-0.095	-0.188	0.093	-0.179	-0.231	0.052	-0.162	-0.184	0.022
	(0.043)	(0.202)	(0.913)	(0.198)	(0.000)	(0.447)	(0.000)	(0.001)	(0.562)	(0.000)	(0.008)	(0.833)

Panel B: Based on Past Three Months of Flows

	1 Month			**3 Months**			**6 Months**			**12 Months**		
$Flow_{t-1}$	High	Low	High-Low	High	Low	High-Low	High	Low	High-Low	High	Low	High-Low
$I(MKT_t = Up)$ (in %)	-0.014	-0.174	0.160	-0.105	-0.224	0.119	0.000	-0.119	0.119	-0.156	-0.267	0.111
	(0.922)	(0.342)	(0.210)	(0.066)	(0.003)	(0.092)	(0.992)	(0.032)	(0.036)	(0.006)	(0.000)	(0.034)
$I(MKT_t = Down)$ (in %)	-0.150	-0.133	-0.017	-0.085	-0.089	0.004	-0.168	-0.161	-0.007	-0.176	-0.124	-0.052
	(0.017)	(0.248)	(0.874)	(0.057)	(0.090)	(0.957)	(0.000)	(0.002)	(0.900)	(0.000)	(0.072)	(0.429)

Panel C: Percentage Flow Portfolios

	1 Month			**3 Months**			**6 Months**			**12 Months**		
$Flow_{t-1}$	High	Low	High-Low	High	Low	High-Low	High	Low	High-Low	High	Low	High-Low
$I(MKT_t = Up)$ (in %)	0.004	-0.176	0.180	-0.049	-0.273	0.224	0.018	-0.139	0.157	-0.108	-0.285	0.177
	(0.978)	(0.336)	(0.340)	(0.566)	(0.002)	(0.043)	(0.680)	(0.006)	(0.057)	(0.048)	(0.000)	(0.012)
$I(MKT_t = Down)$ (in %)	-0.188	-0.098	-0.090	-0.091	-0.096	0.005	-0.156	-0.183	0.027	-0.162	-0.151	-0.011
	(0.012)	(0.431)	(0.576)	(0.117)	(0.047)	(0.964)	(0.000)	(0.001)	(0.734)	(0.000)	(0.017)	(0.900)

Panel D: Three-Factor Model

	1 Month			**3 Months**			**6 Months**			**12 Months**		
$Flow_{t-1}$	High	Low	High-Low	High	Low	High-Low	High	Low	High-Low	High	Low	High-Low
$I(MKT_t = Up)$ (in %)	-0.020	-0.162	0.142	-0.069	-0.241	0.172	0.002	-0.158	0.160	-0.092	-0.184	0.092
	(0.609)	(0.226)	(0.337)	(0.212)	(0.000)	(0.034)	(0.967)	(0.001)	(0.008)	(0.002)	(0.000)	(0.060)
$I(MKT_t = Down)$ (in %)	-0.036	-0.135	0.099	-0.013	-0.135	0.122	-0.082	-0.159	0.077	-0.071	-0.132	0.061
	(0.820)	(0.297)	(0.451)	(0.856)	(0.001)	(0.131)	(0.196)	(0.002)	(0.193)	(0.299)	(0.068)	(0.359)

Table 7: **Performance of Flow-Based Portfolios: Impact of Transaction Costs**

We divide all funds with respect to their characteristics. Panel A reports results for low-momentum funds, Panel B for high-momentum funds, Panel C for low-turnover funds, and Panel D for high-turnover funds. For each sample separately, each month, we construct portfolios of funds based on their dollar flows. *High* denotes the return on the equally weighted portfolio of funds which received flows that are higher than the median flow in a given period; *Low* is the return on the equally weighted portfolio of funds which received flows that are lower than the median flow in a given period. Both returns are regressed on a set of four factors: market premium (MKTPREM), size (SMB), value (HML), and momentum (UMD), and their interactions with two indicator functions: $I(MKT_t = Up)$ equals one when the three-month moving average of market excess return is higher than the 75th percentile of the historical three-month moving average of market returns (starting Q3 of 1926); and zero otherwise. $I(MKT_t = Down)$ equals one when the three-month moving average of market excess return is lower than the 25th percentile of the historical three-month moving average of market returns (starting Q3 of 1926); and zero otherwise. Columns (1)-(2) consider monthly returns one month ahead, columns (3)-(4) monthly returns three months ahead, columns (5)-(6) monthly returns six months ahead, and columns (7)-(8) monthly returns twelve months ahead. Standard errors (in parentheses) are adjusted for autocorrelation up to 12 lags using the procedure as in Newey and West (1987). Each panel reports monthly returns along with their p-values (in parentheses) on portfolios which condition on both market conditions and fund flows. Each panel also reports the results of the F-test of the differences between the respective portfolios. The data cover the period 1980 to 2005.

Panel A: Low-Momentum Funds

	1 Month			**3 Months**			**6 Months**			**12 Months**		
$Flow_{t-1}$	High	Low	High-Low	High	Low	High-Low	High	Low	High-Low	High	Low	High-Low
$I(MKT_t = Up)$ (in %)	-0.144	-0.284	0.140	-0.117	-0.289	0.172	-0.097	-0.206	0.109	-0.311	-0.400	0.089
	(0.300)	(0.031)	(0.194)	(0.140)	(0.000)	(0.005)	(0.105)	(0.005)	(0.046)	(0.002)	(0.001)	(0.140)
$I(MKT_t = Down)$ (in %)	0.110	0.099	0.011	0.204	0.137	0.077	0.144	0.074	0.070	-0.073	-0.132	0.059
	(0.450)	(0.437)	(0.906)	(0.047)	(0.135)	(0.180)	(0.279)	(0.510)	(0.192)	(0.622)	(0.299)	(0.256)

Panel B: High-Momentum Funds

	1 Month			**3 Months**			**6 Months**			**12 Months**		
$Flow_{t-1}$	High	Low	High-Low	High	Low	High-Low	High	Low	High-Low	High	Low	High-Low
$I(MKT_t = Up)$ (in %)	0.137	-0.073	0.210	-0.013	-0.216	0.203	0.038	-0.160	0.198	-0.095	-0.199	0.104
	(0.380)	(0.707)	(0.141)	(0.854)	(0.004)	(0.010)	(0.430)	(0.000)	(0.001)	(0.037)	(0.011)	(0.074)
$I(MKT_t = Down)$ (in %)	-0.268	-0.346	0.078	-0.173	-0.244	0.071	-0.252	-0.288	0.036	-0.176	-0.188	0.012
	(0.006)	(0.032)	(0.523)	(0.023)	(0.000)	(0.364)	(0.000)	(0.000)	(0.545)	(0.000)	(0.001)	(0.870)

Panel C: Low-Turnover Funds

	1 Month			**3 Months**			**6 Months**			**12 Months**		
$Flow_{t-1}$	High	Low	High-Low	High	Low	High-Low	High	Low	High-Low	High	Low	High-Low
$I(MKT_t = Up)$ (in %)	-0.085	-0.152	0.067	-0.136	-0.322	0.186	-0.063	-0.241	0.178	-0.247	-0.332	0.085
	(0.510)	(0.349)	(0.601)	(0.020)	(0.000)	(0.011)	(0.138)	(0.001)	(0.020)	(0.000)	(0.000)	(0.096)
$I(MKT_t = Down)$ (in %)	-0.118	-0.147	0.029	-0.033	-0.071	0.038	-0.107	-0.139	0.038	-0.164	-0.194	0.030
	(0.038)	(0.115)	(0.787)	(0.534)	(0.049)	(0.604)	(0.010)	(0.061)	(0.576)	(0.000)	(0.000)	(0.639)

Panel D: High-Turnover Funds

	1 Month			**3 Months**			**6 Months**			**12 Months**		
$Flow_{t-1}$	High	Low	High-Low	High	Low	High-Low	High	Low	High-Low	High	Low	High-Low
$I(MKT_t = Up)$ (in %)	0.034	-0.111	0.145	-0.001	-0.195	0.194	0.085	-0.128	0.213	-0.044	-0.170	0.126
	(0.881)	(0.571)	(0.419)	(0.993)	(0.011)	(0.061)	(0.179)	(0.029)	(0.005)	(0.443)	(0.036)	(0.066)
$I(MKT_t = Down)$ (in %)	-0.194	-0.148	0.046	-0.068	-0.194	0.126	-0.187	-0.220	0.033	-0.149	-0.159	0.010
	(0.030)	(0.357)	(0.766)	(0.444)	(0.000)	(0.223)	(0.011)	(0.001)	(0.663)	(0.041)	(0.122)	(0.910)

Table 8: **Performance of Flow-Based Portfolios: Within-Style Analysis**

We divide all funds with respect to their investment style. Panel A reports results for value funds, Panel B for growth funds, Panel C for small-cap funds, and Panel D for large-cap funds. For each sample separately, each month, we construct portfolios of funds based on their dollar flows. *High* denotes the return on the equally weighted portfolio of funds which received flows that are higher than the median flow in a given period; *Low* is the return on the equally weighted portfolio of funds which received flows that are lower than the median flow in a given period. Both returns are regressed on a set of four factors: market premium (MKTPREM), size (SMB), value (HML), and momentum (UMD), and their interactions with two indicator functions: $I(MKT_t = Up)$ equals one when the three-month moving average of market excess return is higher than the 75th percentile of the historical three-month moving average of market returns (starting Q3 of 1926); and zero otherwise. $I(MKT_t = Down)$ equals one when the three-month moving average of market excess return is lower than the 25th percentile of the historical three-month moving average of market returns (starting Q3 of 1926); and zero otherwise. Columns (1)-(2) consider monthly returns one month ahead, columns (3)-(4) monthly returns three months ahead, columns (5)-(6) monthly returns six months ahead, and columns (7)-(8) monthly returns twelve months ahead. Standard errors (in parentheses) are adjusted for autocorrelation up to 12 lags using the procedure as in Newey and West (1987). Each panel reports monthly returns along with their p-values (in parentheses) on portfolios which condition on both market conditions and fund flows. Each panel also reports the results of the F-test of the differences between the respective portfolios. The data cover the period 1980 to 2005.

Panel A: Value Funds

	1 Month			**3 Months**			**6 Months**			**12 Months**		
$Flow_{t-1}$	High	Low	High-Low	High	Low	High-Low	High	Low	High-Low	High	Low	High-Low
$I(MKT_t = Up)$ (in %)	-0.007	-0.138	0.145	-0.067	-0.263	0.196	-0.004	-0.122	0.118	-0.286	-0.319	0.033
	(0.974)	(0.284)	(0.214)	(0.548)	(0.003)	(0.003)	(0.940)	(0.055)	(0.014)	(0.001)	(0.001)	(0.349)
$I(MKT_t = Down)$ (in %)	-0.012	-0.045	0.033	0.182	0.093	0.089	0.077	0.034	0.043	-0.016	-0.011	-0.005
	(0.947)	(0.778)	(0.706)	(0.173)	(0.395)	(0.171)	(0.495)	(0.745)	(0.369)	(0.881)	(0.917)	(0.917)

Panel B: Growth Funds

	1 Month			**3 Months**			**6 Months**			**12 Months**		
$Flow_{t-1}$	High	Low	High-Low	High	Low	High-Low	High	Low	High-Low	High	Low	High-Low
$I(MKT_t = Up)$ (in %)	0.002	-0.143	0.145	-0.107	-0.258	0.141	-0.015	-0.174	0.159	-0.160	-0.242	0.082
	(0.988)	(0.444)	(0.328)	(0.135)	(0.000)	(0.071)	(0.796)	(0.001)	(0.014)	(0.002)	(0.002)	(0.166)
$I(MKT_t = Down)$ (in %)	-0.171	-0.180	0.009	-0.088	-0.152	0.064	-0.183	-0.208	0.025	-0.188	-0.183	-0.005
	(0.024)	(0.119)	(0.938)	(0.163)	(0.000)	(0.436)	(0.000)	(0.000)	(0.690)	(0.000)	(0.002)	(0.950)

Panel C: Small-Cap Funds

	1 Month			**3 Months**			**6 Months**			**12 Months**		
$Flow_{t-1}$	High	Low	High-Low	High	Low	High-Low	High	Low	High-Low	High	Low	High-Low
$I(MKT_t = Up)$ (in %)	-0.152	-0.257	0.105	-0.233	-0.406	0.173	-0.078	-0.185	0.107	-0.291	-0.390	0.099
	(0.558)	(0.225)	(0.580)	(0.032)	(0.001)	(0.124)	(0.276)	(0.018)	(0.164)	(0.016)	(0.002)	(0.196)
$I(MKT_t = Down)$ (in %)	-0.047	-0.289	0.242	0.135	0.013	0.122	-0.130	-0.144	0.014	-0.189	-0.250	0.061
	(0.226)	(0.297)	(0.451)	(0.000)	(0.001)	(0.131)	(0.001)	(0.002)	(0.193)	(0.000)	(0.068)	(0.359)

Panel D: Large-Cap Funds

	1 Month			**3 Months**			**6 Months**			**12 Months**		
$Flow_{t-1}$	High	Low	High-Low	High	Low	High-Low	High	Low	High-Low	High	Low	High-Low
$I(MKT_t = Up)$ (in %)	0.038	-0.086	0.124	0.022	-0.179	0.201	0.083	-0.086	0.169	-0.053	-0.185	0.132
	(0.797)	(0.508)	(0.383)	(0.736)	(0.000)	(0.013)	(0.037)	(0.023)	(0.006)	(0.109)	(0.002)	(0.011)
$I(MKT_t = Down)$ (in %)	-0.132	-0.092	-0.040	-0.109	-0.142	0.033	-0.157	-0.167	0.010	-0.162	-0.142	-0.020
	(0.026)	(0.433)	(0.742)	(0.010)	(0.001)	(0.683)	(0.000)	(0.000)	(0.863)	(0.000)	(0.010)	(0.762)

Table 9: **Survival Rates in Flow-Based Portfolios**

Each month we construct portfolios of funds based on their dollar flows. *High* denotes the portfolio of funds which received flows that are higher than the median flow in a given period; *Low* is the portfolio of funds which received flows that are lower than the median flow in a given period. Both portfolios are tracked over one, three, six, and twelve months, conditional on two indicator functions: $I(MKT_t = Up)$ equals one when the three-month moving average of market excess return is higher than the 75th percentile of the historical three-month moving average of market excess returns (starting Q3 of 1926); and zero otherwise. $I(MKT_t = Down)$ equals one when the three-month moving average of market excess return is lower than the 25th percentile of the historical three-month moving average of market returns (starting Q3 of 1926); and zero otherwise. We estimate average survival rates as a time-series average of the ratio of the number of funds that appear in the beginning and the end of the investment period and the number of funds that appear in the beginning of the investment period. We report the differences in average survival rates along with their p-values (in parentheses). The data cover the period 1980 to 2005.

	1 Month			**3 Months**			**6 Months**			**12 Months**		
$Flow_{t-1}$	High	Low	High-Low	High	Low	High-Low	High	Low	High-Low	High	Low	High-Low
$I(MKT_t = Up)$ (in %)	98.58	98.52	0.06	96.60	96.64	-0.05	94.45	94.00	0.45	88.51	87.49	1.02
	(2.43)	(2.40)	(0.735)	(3.45)	(2.76)	(0.906)	(4.56)	(3.53)	(0.461)	(4.47)	(3.82)	(0.258)
$I(MKT_t = Down)$ (in %)	98.17	98.71	-0.54	94.87	95.26	-0.38	89.93	90.53	-0.60	84.74	85.66	-0.92
	(2.19)	(1.77)	(0.035)	(5.17)	(4.47)	(0.393)	(5.93)	(5.84)	(0.385)	(5.91)	(6.26)	(0.241)

Table 10: **Flow-Performance Relationship and Market Conditions: Based on Investors' Type**

We divide all funds into institutional and retail categories and estimate regression equations for each group separately. The dependent variable is fund flow ($Flow$). Bottom row provides the F-test along with its p-values of the differences between coefficients on $I(MKT_t = Up)$ and $I(MKT_t = Down)$. Our controls include Performance, Log(Age), Log(TNA), Expenses, Flow, Turnover, Value, Size, and Momentum. Flow, Performance, and Turnover have been winsorized at the 1% level. All variables are defined in Table 2. $I(MKT_t = Up)$ equals one when the three-month moving average of market excess return is higher than the 75th percentile of the historical three-month moving average of market returns (starting Q3 of 1926); and zero otherwise. $I(MKT_t = Down)$ equals one when the three-month moving average of market excess return is lower than the 25th percentile of the historical three-month moving average of market returns (starting Q3 of 1926); and zero otherwise. Standard errors (in parentheses) are clustered by fund and time. A bottom panel reports an F-test of differences in coefficients on $I(MKT_t = Up)$ and $I(MKT_t = Down)$ along with their p-values (in parentheses). The data cover the period 1980 to 2005.

	Flows			
	Institutional		**Retail**	
Performance	0.169	0.124	0.254	0.201
	(0.032)	(0.028)	(0.027)	(0.024)
Log(Age)	-0.006	-0.019	-0.007	-0.013
	(0.001)	(0.002)	(0.001)	(0.002)
Log(TNA)	0.001	-0.002	0.000	-0.003
	(0.001)	(0.001)	(0.000)	(0.001)
Expenses	-0.074	0.344	-0.190	0.233
	(0.158)	(0.324)	(0.168)	(0.227)
Turnover	-0.002	-0.000	-0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Loads	0.060	-0.020	-0.002	-0.023
	(0.027)	(0.033)	(0.019)	(0.039)
Value	0.005	0.002	0.005	-0.000
	(0.001)	(0.002)	(0.001)	(0.001)
Size	-0.000	-0.001	-0.001	-0.001
	(0.001)	(0.002)	(0.001)	(0.001)
Momentum	0.008	0.008	0.006	0.009
	(0.001)	(0.001)	(0.001)	(0.001)
Performance x	0.021	0.020	0.100	0.112
$I(MKT_t = Up)$	(0.092)	(0.088)	(0.096)	(0.092)
Performance x	-0.070	-0.042	-0.187	-0.160
$I(MKT_t = Down)$	(0.067)	(0.065)	(0.059)	(0.057)
$I(MKT_t = Up)$	0.006	0.006	0.007	0.007
	(0.005)	(0.005)	(0.005)	(0.004)
$I(MKT_t = Down)$	-0.011	-0.011	-0.011	-0.011
	(0.004)	(0.004)	(0.004)	(0.004)
Constant	-0.028	0.023	-0.003	0.027
	(0.009)	(0.014)	(0.007)	(0.012)
Observations	47,702	47,702	144,019	144,019
R^2	0.02	0.09	0.03	0.10
Fund Fixed-Effects	No	Yes	No	Yes

F-test: $I(MKT_t = Up) \times Perf. = I(MKT_t = Down) \times Perf.$				
Difference	0.091	0.062	0.287	0.272
	(0.181)	(0.546)	(0.000)	(0.009)

Table 11: **Performance of Flow-Based Portfolios: Based on Investors' Type**

We divide all funds into retail and institutional categories. For each category separately, each month, we construct portfolios of funds based on their last month dollar flows. *High* denotes the return on the equally weighted portfolio of funds which received flows that are higher than the median flow in a given period; *Low* is the return on the equally weighted portfolio of funds which received flows that are lower than the median flow in a given period. Both returns are regressed on a set of four factors: market premium (MKTPREM), size (SMB), value (HML), and momentum (UMD), and their interactions with two indicator functions: $I(MKT_t = Up)$ equals one when the three-month moving average of market excess return is higher than the 75th percentile of the historical three-month moving average of market returns (starting Q3 of 1926); and zero otherwise. $I(MKT_t = Down)$ equals one when the three-month moving average of market excess return is lower than the 25th percentile of the historical three-month moving average of market returns (starting Q3 of 1926); and zero otherwise. Columns (1)-(2) consider monthly returns one month ahead, columns (3)-(4) monthly returns three months ahead, columns (5)-(6) monthly returns six months ahead, and columns (7)-(8) monthly returns twelve months ahead. Standard errors (in parentheses) are adjusted for autocorrelation up to 12 lags using the procedure as in Newey and West (1987). Panel A reports the results for retail investors and Panel B presents the results for institutional investors. A bottom panel of each Panel reports monthly returns along with their p-values (in parentheses) on portfolios which condition on both market conditions and fund flows. The panel also reports the results of the F-test of the differences between the respective portfolios. The data cover the period 1980 to 2005.

Panel A: Retail Investors

	1 Month		**3 Months**		**6 Months**		**12 Months**	
$Flow_{t-1}$	High	Low	High	Low	High	Low	High	Low
MKTPREM	0.982	0.998	0.972	0.999	0.966	0.975	0.961	0.937
	(0.012)	(0.016)	(0.016)	(0.017)	(0.019)	(0.025)	(0.025)	(0.041)
SMB	0.230	0.097	0.229	0.120	0.226	0.180	0.253	0.178
	(0.015)	(0.049)	(0.019)	(0.055)	(0.022)	(0.038)	(0.034)	(0.049)
HML	-0.062	-0.009	-0.076	0.028	-0.073	0.038	-0.073	0.051
	(-0.025)	(-0.049)	(-0.023)	(0.053)	(-0.023)	(0.050)	(-0.024)	(0.067)
UMD	0.031	-0.039	0.027	-0.058	0.044	-0.008	0.080	0.041
	(0.013)	(-0.030)	(0.010)	(-0.033)	(0.015)	(-0.022)	(0.021)	(0.030)
MKTPREM x	-0.032	-0.028	-0.049	-0.009	-0.101	-0.018	-0.015	0.021
$I(MKT_t = Up)$	(-0.034)	(-0.039)	(-0.031)	(-0.022)	(-0.048)	(-0.033)	(-0.034)	(0.042)
MKTPREM x	0.074	-0.014	0.055	0.013	0.084	0.120	0.042	0.129
$I(MKT_t = Down)$	(0.023)	(-0.039)	(0.025)	(0.029)	(0.030)	(0.042)	(0.027)	(0.047)
SMB x	-0.080	0.071	-0.004	0.092	0.062	0.045	-0.007	0.030
$I(MKT_t = Up)$	(-0.045)	(0.056)	(-0.042)	(0.052)	(0.053)	(0.041)	(-0.040)	(0.046)
SMB x	-0.032	0.049	-0.004	-0.040	-0.023	-0.139	-0.067	-0.107
$I(MKT_t = Down)$	(-0.034)	(0.057)	(-0.048)	(-0.053)	(-0.050)	(-0.058)	(-0.052)	(-0.069)
HML x	-0.058	-0.102	-0.013	-0.075	-0.086	-0.155	0.063	-0.012
$I(MKT_t = Up)$	(-0.067)	(-0.080)	(-0.029)	(-0.063)	(-0.046)	(-0.061)	(0.052)	(-0.072)
HML x	0.115	0.099	0.107	0.063	0.125	0.152	0.045	0.093
$I(MKT_t = Down)$	(0.033)	(0.059)	(0.034)	(0.041)	(0.032)	(0.038)	(0.044)	(0.063)
UMD x	-0.018	0.032	-0.040	0.081	-0.067	-0.016	-0.013	0.067
$I(MKT_t = Up)$	(-0.076)	(0.062)	(-0.047)	(0.038)	(-0.030)	(-0.023)	(-0.071)	(0.105)
UMD x	0.048	0.051	0.041	0.046	0.040	0.035	0.018	-0.004
$I(MKT_t = Down)$	(0.029)	(0.033)	(0.020)	(0.027)	(0.041)	(0.039)	(0.030)	(-0.030)
$I(MKT_t = Up)$	0.000	-0.001	0.000	-0.002	0.001	-0.001	0.000	-0.001
	(0.002)	(-0.002)	(0.001)	(-0.001)	(0.001)	(-0.001)	(0.001)	(-0.001)
$I(MKT_t = Down)$	-0.001	-0.001	0.000	0.000	-0.001	-0.001	0.000	-0.001
	(-0.001)	(-0.002)	(0.001)	(0.001)	(-0.000)	(-0.001)	(0.001)	(-0.001)
Constant	0.000	0.000	0.000	0.000	0.000	-0.001	-0.001	-0.001
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(-0.001)	(-0.000)	(-0.001)
Observations	307	307	305	305	302	302	296	296
R^2	0.97	0.97	0.97	0.96	0.97	0.97	0.97	0.95

	1 Month			**3 Months**			**6 Months**			**12 Months**		
$Flow_{t-1}$	High	Low	High-Low	High	Low	High-Low	High	Low	High-Low	High	Low	High-Low
$I(MKT_t = Up)$ (in %)	0.040	-0.101	0.141	0.032	-0.235	0.267	0.106	-0.110	0.216	-0.046	-0.200	0.154
	(0.819)	(0.577)	(0.361)	(0.653)	(0.001)	(0.002)	(0.020)	(0.024)	(0.001)	(0.396)	(0.010)	(0.010)
$I(MKT_t = Down)$ (in %)	-0.065	-0.111	0.046	0.015	-0.070	0.085	-0.084	-0.135	0.051	-0.085	-0.124	0.039
	(0.297)	(0.394)	(0.726)	(0.842)	(0.143)	(0.320)	(0.122)	(0.017)	(0.430)	(0.112)	(0.052)	(0.605)

Panel B: Institutional Investors

	1 Month		3 Months		6 Months		12 Months	
$Flow_{t-1}$	High	Low	High	Low	High	Low	High	Low
MKTPREM	0.974	0.963	0.958	0.975	0.959	0.966	0.949	0.935
	(0.012)	(0.019)	(0.011)	(0.020)	(0.018)	(0.020)	(0.025)	(0.032)
SMB	0.230	0.132	0.237	0.131	0.228	0.196	0.292	0.206
	(0.025)	(0.047)	(0.027)	(0.051)	(0.032)	(0.032)	(0.034)	(0.033)
HML	-0.021	-0.005	-0.013	0.010	-0.023	0.034	-0.019	0.039
	(-0.024)	(-0.047)	(-0.024)	(0.050)	(-0.028)	(0.042)	(-0.030)	(0.056)
UMD	0.002	-0.035	0.000	-0.060	0.018	-0.017	0.053	0.010
	(0.014)	(-0.028)	(0.014)	(-0.029)	(0.016)	(-0.017)	(0.023)	(0.023)
MKTPREM x	-0.098	-0.009	-0.052	-0.057	-0.073	-0.060	0.012	0.028
$I(MKT_t = Up)$	(-0.044)	(-0.033)	(-0.035)	(-0.026)	(-0.050)	(-0.031)	(0.035)	(0.039)
MKTPREM x	0.056	-0.005	0.068	0.020	0.065	0.063	0.060	0.050
$I(MKT_t = Down)$	(0.035)	(-0.036)	(0.029)	(0.032)	(0.031)	(0.036)	(0.024)	(0.039)
SMB x	-0.040	0.097	0.078	0.166	0.114	0.111	0.005	0.025
$I(MKT_t = Up)$	(-0.043)	(0.050)	(0.048)	(0.050)	(0.050)	(0.038)	(0.040)	(0.040)
SMB x	-0.021	0.034	-0.003	-0.002	0.026	-0.109	-0.012	-0.066
$I(MKT_t = Down)$	(-0.030)	(0.052)	(-0.044)	(-0.051)	(0.058)	(-0.054)	(-0.043)	(-0.053)
HML x	-0.150	-0.093	-0.033	-0.067	-0.072	-0.142	0.091	0.048
$I(MKT_t = Up)$	(-0.078)	(-0.081)	(-0.030)	(-0.061)	(-0.055)	(-0.056)	(0.053)	(0.069)
HML x	0.098	0.098	0.082	0.102	0.108	0.159	0.058	0.072
$I(MKT_t = Down)$	(0.031)	(0.057)	(0.036)	(0.043)	(0.043)	(0.036)	(0.047)	(0.054)
UMD x	-0.044	0.034	-0.025	0.108	-0.039	0.007	0.027	0.094
$I(MKT_t = Up)$	(-0.055)	(0.054)	(-0.045)	(0.036)	(-0.023)	(0.024)	(0.069)	(0.104)
UMD x	0.060	0.042	0.055	0.056	0.068	0.031	0.043	0.007
$I(MKT_t = Down)$	(0.025)	(0.028)	(0.021)	(0.029)	(0.040)	(0.039)	(0.033)	(0.028)
$I(MKT_t = Up)$	0.000	-0.002	-0.001	-0.002	0.000	-0.001	-0.001	-0.002
	(0.002)	(-0.002)	(-0.001)	(-0.001)	(0.001)	(-0.001)	(-0.001)	(-0.001)
$I(MKT_t = Down)$	-0.002	-0.001	-0.001	-0.001	-0.002	-0.001	-0.001	-0.001
	(-0.001)	(-0.001)	(-0.001)	(-0.001)	(-0.001]	(-0.001)	(-0.000)	(-0.001)
Constant	-0.001	-0.001	-0.001	-0.001	-0.001	-0.002	-0.002	-0.002
	(-0.001)	(-0.001)	(-0.000)	(-0.001)	(-0.000)	(-0.000)	(-0.001)	(-0.000)
Observations	307	307	305	305	302	302	296	296
R^2	0.97	0.97	0.97	0.96	0.97	0.97	0.97	0.95

	1 Month			3 Months			6 Months			12 Months		
$Flow_{t-1}$	High	Low	High-Low	High	Low	High-Low	High	Low	High-Low	High	Low	High-Low
$I(MKT_t = Up)$ (in %)	-0.081	-0.318	0.237	-0.228	-0.348	0.120	-0.171	-0.216	0.055	-0.324	-0.360	0.038
	(0.597)	(0.020)	(0.146)	(0.002)	(0.000)	(0.176)	(0.003)	(0.000)	(0.493)	(0.000)	(0.000)	(0.534)
$I(MKT_t = Down)$ (in %)	-0.292	-0.251	-0.041	-0.249	-0.244	-0.005	-0.333	-0.283	-0.050	-0.315	-0.243	-0.072
	(0.001)	(0.027)	(0.763)	(0.000)	(0.000)	(0.954)	(0.000)	(0.000)	(0.442)	(0.000)	(0.000)	(0.327)

Table 12: **Performance of Flow-Based Portfolios: Based on Fund Age**

We divide all funds with respect to their age. Panel A reports results for funds younger than three years and Panel B for funds older than nine years (median value of the fund sample). For each sample separately, each month, we construct portfolios of funds based on their dollar flows. *High* denotes the return on the equally weighted portfolio of funds which received flows that are higher than the median flow in a given period; *Low* is the return on the equally weighted portfolio of funds which received flows that are lower than the median flow in a given period. Both returns are regressed on a set of four factors: market premium (MKTPREM), size (SMB), value (HML), and momentum (UMD), and their interactions with two indicator functions: $I(MKT_t = Up)$ equals one when the three-month moving average of market excess return is higher than the 75th percentile of the historical three-month moving average of market returns (starting Q3 of 1926); and zero otherwise. $I(MKT_t = Down)$ equals one when the three-month moving average of market excess return is lower than the 25th percentile of the historical three-month moving average of market returns (starting Q3 of 1926); and zero otherwise. Each panel reports monthly returns along with their p-values (in parentheses) on portfolios which condition on both market conditions and fund flows. Columns (1)-(2) consider monthly returns one month ahead, columns (3)-(4) monthly returns three months ahead, columns (5)-(6) monthly returns six months ahead, and columns (7)-(8) monthly returns twelve months ahead. Standard errors (in parentheses) are adjusted for autocorrelation up to 12 lags using the procedure as in Newey and West (1987). Each panel also reports the results of the F-test of the differences between the respective portfolios. The data cover the period 1980 to 2005.

Fund Age<= 3

	1 Month			**3 Months**			**6 Months**			**12 Months**		
$Flow_{t-1}$	High	Low	High-Low	High	Low	High-Low	High	Low	High-Low	High	Low	High-Low
$I(MKT_t = Up)$ (in %)	0.046	-0.553	0.599	0.176	-0.289	0.465	-0.024	-0.043	0.019	-0.085	-0.275	0.190
	(0.855)	(0.000)	(0.015)	(0.185)	(0.000)	(0.001)	(0.808)	(0.704)	(0.892)	(0.394)	(0.054)	(0.075)
$I(MKT_t = Down)$ (in %)	-0.076	-0.168	0.092	-0.132	-0.250	0.118	-0.247	-0.278	0.031	-0.205	-0.241	0.036
	(0.595)	(0.302)	(0.661)	(0.029)	(0.005)	(0.382)	(0.003)	(0.042)	(0.812)	(0.006)	(0.031)	(0.783)

Fund Age>= 9

	1 Month			**3 Months**			**6 Months**			**12 Months**		
$Flow_{t-1}$	High	Low	High-Low	High	Low	High-Low	High	Low	High-Low	High	Low	High-Low
$I(MKT_t = Up)$ (in %)	-0.024	-0.112	0.088	-0.075	-0.228	0.153	0.016	-0.126	0.110	-0.168	-0.246	0.078
	(0.877)	(0.432)	(0.550)	(0.216)	(0.000)	(0.060)	(0.677)	(0.006)	(0.026)	(0.004)	(0.001)	(0.193)
$I(MKT_t = Down)$ (in %)	-0.152	-0.172	0.020	-0.066	-0.123	0.057	-0.133	-0.163	0.030	-0.179	-0.187	0.008
	(0.016)	(0.175)	(0.873)	(0.336)	(0.010)	(0.482)	(0.006)	(0.003)	(0.647)	(0.000)	(0.002)	(0.912)

Table 13: **Fund Strategies and Market Conditions**

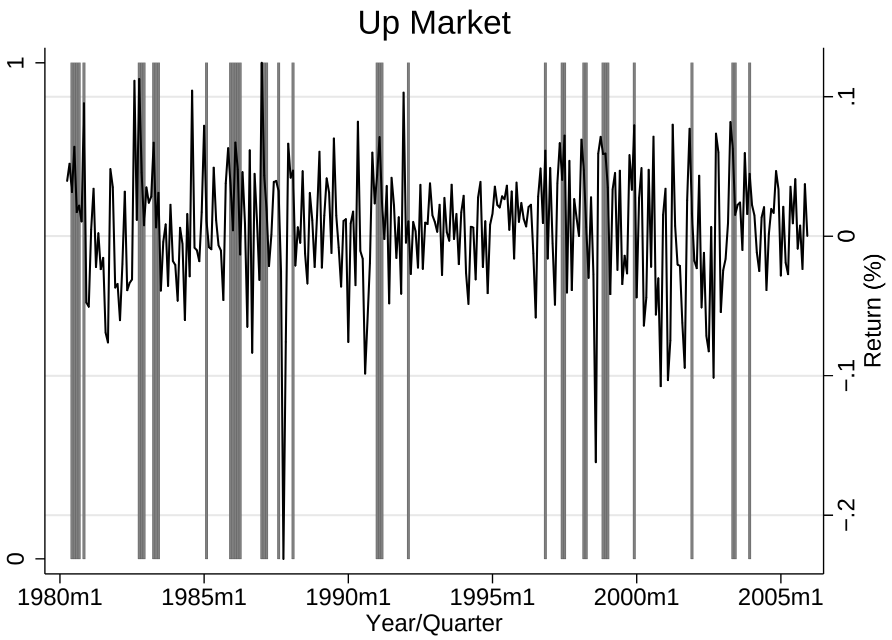
The dependent variables are *BetaDeviation* in Columns (1) and (2), *SectorDeviation* in Columns (3) and (4) and *UnsystematicDeviation* in Columns (5) and (6). Bottom row provides the F-test along with its p-values of the differences between coefficients on $I(MKT_t = Up)$ and $I(MKT_t = Down)$. Our controls include Performance, Log(Age), Log(TNA), Expenses, Flow, Turnover, Value, Size, and Momentum. Flow, Performance, and Turnover have been winsorized at the 1% level. All variables are defined in Table 2. $I(MKT_t = Up)$ equals one when the three-month moving average of market excess return is higher than the 75th percentile of the historical three-month moving average of market returns (starting Q3 of 1926); and zero otherwise. $I(MKT_t = Down)$ equals one when the three-month moving average of market excess return is lower than the 25th percentile of the historical three-month moving average of market returns (starting Q3 of 1926); and zero otherwise. Standard errors (in parentheses) are clustered by fund and time. A bottom panel reports an F-test of differences in coefficients on $I(MKT_t = Up)$ and $I(MKT_t = Down)$ along with their p-values (in parentheses). The data cover the period 1980 to 2005.

	Beta Deviation		Sector Deviation		Unsystematic Deviation	
Performance	-0.196	-0.167	0.056	0.024	-0.139	-0.099
	(0.054)	(0.032)	(0.052)	(0.024)	(0.192)	(0.159)
Log(Age)	0.001	0.007	-0.022	-0.022	-0.011	-0.031
	(0.002)	(0.003)	(0.002)	(0.001)	(0.005)	(0.007)
Log(TNA)	-0.001	-0.005	-0.007	-0.003	-0.009	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Expenses	2.161	-0.428	1.739	-0.674	4.835	0.040
	(0.513)	(0.193)	(0.326)	(0.187)	(0.851)	(0.788)
Flow	-0.015	0.001	0.011	-0.014	0.029	0.024
	(0.012)	(0.008)	(0.012)	(0.007)	(0.037)	(0.029)
Turnover	0.015	0.003	-0.002	-0.003	0.048	0.028
	(0.003)	(0.001)	(0.002)	(0.001)	(0.007)	(0.004)
Value	0.004	0.003	0.011	0.002	-0.026	-0.025
	(0.005)	(0.001)	(0.004)	(0.001)	(0.009)	(0.006)
Size	-0.010	-0.007	-0.013	-0.007	-0.029	-0.036
	(0.002)	(0.002)	(0.002)	(0.001)	(0.005)	(0.007)
Momentum	-0.002	-0.009	0.002	0.002	0.003	0.002
	(0.003)	(0.002)	(0.003)	(0.001)	(0.008)	(0.006)
$I(MKT_t = Up)$	-0.002	-0.002	0.003	0.003	-0.005	-0.007
	(0.005)	(0.004)	(0.005)	(0.003)	(0.006)	(0.006)
$I(MKT_t = Down)$	0.011	0.010	0.003	0.003	0.011	0.010
	(0.004)	(0.004)	(0.005)	(0.004)	(0.006)	(0.005)
Constant	0.146	0.199	0.219	0.281	0.787	0.897
	(0.026)	(0.010)	(0.022)	(0.007)	(0.048)	(0.042)
Observations	167,584	167,584	58,144	58,144	167,584	167,584
R^2	0.03	0.39	0.07	0.64	0.02	0.10
Fund Fixed-Effects	No	Yes	No	Yes	No	Yes

	F-test: $I(MKT_t = Up) = I(MKT_t = Down)$					
Difference	-0.013	-0.012	-0.000	0.000	-0.016	-0.018
	(0.000)	(0.032)	(0.821)	(0.894)	(0.001)	(0.017)

Figure 1: Market Return and Conditioning Variables

This figure presents means the monthly market excess returns (solid black line) with the different market conditions. In the upper panel, months defined as $I(MKT_t = Up)$ are shaded gray. These are the months in which the three-month moving average excess returns is higher than the 75th percentile of the historical three-month moving average of market excess returns. In the lower panel, months defined $I(MKT_t = Down)$ are shaded gray. These are the months in which the three-month moving average excess returns is lower than the 25th percentile of the historical market excess return. The data cover the period 1980 to 2005.



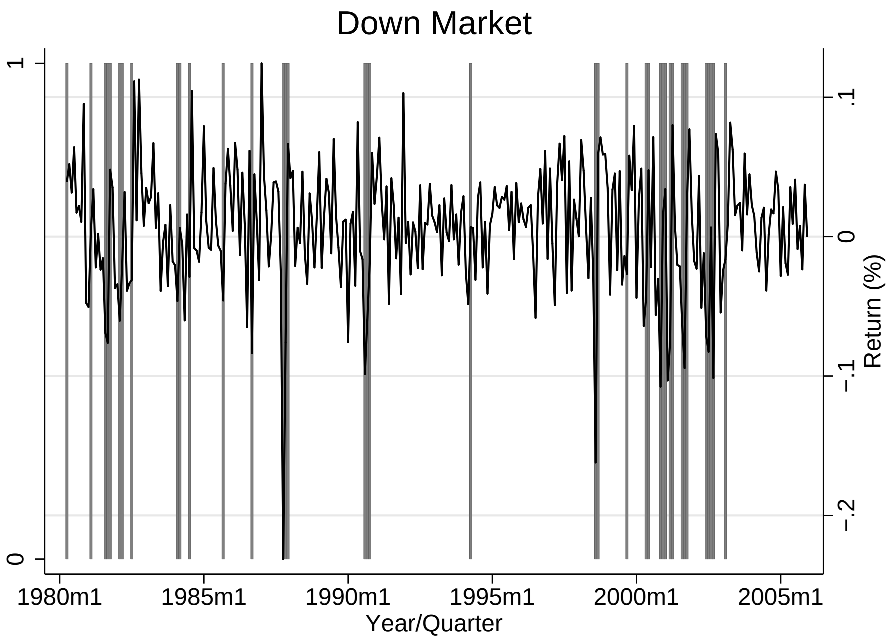


Figure 2: Performance Persistence vs. Market Conditions

This figure depicts the three, six, nine, and twelve months performance of one-month alpha-sorted funds. Alpha is computed using a standard four-factor model, regressed over a 36-month period. Funds are sorted into five decile groups such that "Quintile 1" ("Quintile 5") refers to the best (worst) past alpha funds. The average alpha during the one month sorting period is reported as "Month 0". The upper panel shows the results for funds sorted following months in which $I(MKT_t = Up)$, which are defined as months in which the three-month moving average excess returns is higher than the 75th percentile of the historical three-month moving average of market excess returns. The lower panel shows the results for funds sorted following months in which $I(MKT_t = Down)$, which are defined as months in which the three-month moving average excess returns is lower than the 25th percentile of the historical market excess return. The data cover the period 1980 to 2005.