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

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**Abstract**

We provide new evidence that mutual fund investors do not allocate their capital efficiently after periods of high market returns. If fund investors allocate capital across mutual funds efficiently, then the relative performance of funds should be unpredictable, yet we find that fund relative performance is unpredictable after periods of low market returns but is predictable after periods of high market returns. The asymmetric predictability in relative performance cannot be fully explained by time-varying differences in transaction costs or style exposures among funds, or by sample selection. Consistent with the hypothesis that the asymmetric predictability in relative performance may be driven by unsophisticated investors' mistakes when allocating capital, we find that performance predictability is more pronounced for funds catering to retail investors than for funds catering to institutional investors.

Traditional asset pricing models typically assume that rational investors do not systematically leave money on the table. But over the last few decades a large number of empirical studies document substantial deviations from frictionless rationality in the behavior of various market participants. Understanding the source and nature of such deviations is important for understanding asset returns. Anecdotal evidence and academic research suggest that swings in economic activity may be related to economically significant differences in investors' behavior. For example, popular press has widely argued that recent financial crisis brought about irrationally large downsizing of equity positions in the retirement accounts of retail investors, a fact commonly attributed to the investors' overreaction in bad market conditions. On the other hand, 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) show that unsophisticated investors learn more and make fewer mistakes in periods of low market returns. Documenting such state-dependent deviations from rationality in a group of individual investors offers a promising path to a better understanding of investors' behavior and financial markets. Of equal importance is whether deviations from rational decision making lead to systematic differences in the returns in economically large markets, and more specifically whether and how the degree of efficiency of capital allocation depends on market conditions.

We provide new empirical evidence that investors' capital allocations are not always fully efficient: At times, the returns to marginal dollar allocated by investors may deviate from the returns implied by the rational equilibrium condition. We focus on investors in the U.S. mutual fund industry because the industry is large and economically important, and because the allocation decisions in the fund industry represent the collective decisions of a large set of households.[1] The fund industry also provides a rich setting where we can jointly observe the level of returns and capital flows.

[1] By the end of 2009, 43 percent of U.S. households owned mutual fund shares and invested a total of 11 trillion dollars in U.S. mutual funds. During the same year, a record-high 883 billion dollars flowed into U.S. mutual funds. See the 2009 Investment Company Factbook (http://www.icifactbook.org.)

To identify deviations from rational behavior by fund investors, we use the Berk and Green (2004) model as a benchmark for a rational equilibrium in the mutual fund industry. The model shows that if asset management has decreasing returns to scale and if fund investors are rational, then fund flows should adjust to equalize expected performance *across* funds, thus resulting in no predictability of relative fund performance in the cross section of funds. Given the empirical evidence in Chen et al. (2004) and Edelen, Evans, and Kadlec (2007) of decreasing returns in asset management, the empirical relationship between fund flows, past abnormal returns, and future abnormal returns across funds is informative about how efficiently the investors process and use information.

We study the capital allocation decisions using a large sample of equity 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. We examine conditional cross-sectional predictability of fund returns using two sets of conditioning information: past performance and past flows. 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 find a qualitatively similar pattern when we sort funds based on past fund flows. Building on 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 earns 1.3% to 2.5% higher annualized abnormal return than the portfolio of low-flow funds after periods of high market returns. But both portfolios earn 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. The 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 consider a number of explanations for our findings. First, fund investors may be subject to asymmetric trading frictions in up and down markets, leading them to rationally refrain from switching between funds. Most trading frictions such as load fees and lock-ins appear to be either non-binding for at least one investor or 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 degree of momentum tilt in a fund portfolio as proxies for the average effective capital gains tax liability, we do find some support for the capital gains tax explanation but the tax explanation is unlikely to fully account for our findings.

Second, the observed patterns in performance predictability 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, then switching between the two types of funds would be equivalent to investors trading 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 this 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, 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. Comparing retail funds with institutional funds, as a proxy for investors' sophistication, we find that the asymmetry in predictability is concentrated among funds that cater to retail investors. This finding is consistent with the results in Bailey, Kumar, and Ng (2010) who show that on average more sophisticated investors earn higher returns on their mutual fund investments. Also, performance predictability is substantially stronger for young funds, consistent with the idea that young funds cater to less sophisticated investors.

Given that after periods of high market returns fund investors do not seem to process information efficiently, fund managers' incentives to exert costly effort and acquire information about investment opportunities should be weaker after periods of high market returns. We therefore study cross-sectional differences in the managers' investment strategies across market conditions. We use activeness measures similar to those in Chevalier and Ellison (1999) and show that fund managers are more active after periods of low market returns than they are 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 the empirical work on trading behavior of individual investors. 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 and of full-service brokers. Our results imply that retail fund investors do not process and act on information efficiently after periods of high market returns.

Second, our work is also related to 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, or how efficiently information is processed, may need to be evaluated in a framework that accounts for differences in market conditions.

Third, a recent literature has focused on explaining the time variation in aggregate mutual fund performance. Glode (2010) proposes a model in which mutual fund managers generate good performance in bad states of the economy because investors are willing to pay more for such returns. He shows that such mechanism can lead to negative unconditional performance of the mutual fund industry as a whole. Kacperczyk, van Nieuwerburgh and Veldkamp (2010) show that fund managers are more active and perform better in recessions because of different returns to learning strategies. Pastor and Stambaugh (2010) argue that uncertainty about the industry-wide returns to scale of delegated asset management and the learning associated with it can drive aggregate fund flows and generate variation in the aggregate performance of the asset management industry. In contrast, our work focuses on how investors choose among different funds once they have decided to allocate money to the fund industry, and the resulting effects on the cross section of fund performance across different market conditions. We do not seek to understand the aggregate size of the industry or its performance across different market conditions.

Finally, our empirical results extend the discussion on the value of active management. Carhart (1997) shows that active mutual funds do not outperform passive benchmarks and 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., 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 also provide an economic rationale for the finding.

# 1 Theoretical Framework and Predictions

We use the rational model of mutual fund investment in Berk and Green (2004) (see also Nanda, Narayanan and Warther (2000)) to provide a benchmark of the empirical implications for mutual fund flows and fund performance with rational investors. Berk and Green (2004) study an economy in which rational investors competitively supply capital to the mutual fund industry, in which there is learning about managers' differential ability to generate abnormal returns, and in which there are decreasing returns to scale in generating abnormal 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.

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:

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

With 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 we use in our empirical work 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 in 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 should disappear before financial markets can reach an equilibrium. Berk and Green (2004) provide mechanisms that describe how such an equilibrium can 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 investors behave 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, consider 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.

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 empirical instruments.

## 2 Data

We define three market conditions: Up, Mid, and Down. A market is *Up* when the three-month moving average of the market excess returns for this time period is higher than its historical 75th percentile. A market is *Mid* when the three-month moving average of the market excess returns for this time period is between its historical 25th percentile and 75th percentiles. A market is *Down* 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 $I(MKT_t = Down)$. So, instead of using within-sample percentiles to define up and down markets, we use percentiles from 1926 up to each observation date to estimate possibly well the information investors had about market conditions at the time of their trading. 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.

Our main tests 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. Because we use out-of-sample definitions for market conditions, the number of up market and down market months does not equal to 25% of the number of months.

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 fund sample, we merge the CRSP Survivorship Bias Free Mutual Fund Database with the Thomson Reuters 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 Thomson database also 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 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. 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 $t$. In order to reduce notational clutter, we only use subscripts when necessary for expositional purposes.

Let $R_{i,t}$ denote fund $i$'s monthly return net of expenses at between $t$ and $t+1$. *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 assuming that all cash flows are invested at the end of the period:

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

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 of dollars. *Expenses* is the fund's expense ratio. *Turnover* is the fund's turnover ratio. *Load* is the total load fee.

*Value* is the average value score of all stocks in the fund's portfolio, where each stock is assigned a value score from 1 to 5 based on its book-to-market ratio. *Size* is the average size score of all stocks in the fund's portfolio, where each stock is assigned a size score from 1 to 5 based on its market capitalization. *Momentum* is the average momentum score of all stocks in the fund's portfolio, where each stock is assigned a momentum 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 Carhart (1997) four-factor model.

Table 2 reports summary statistics for our variables; Panel A for the entire sample, Panel B for up markets only, and Panel C for down markets only. Most of the summary statistics in the unconditional sample are consistent with those reported in previous studies, giving 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 increase in down markets.

# 3 Fund Flows Predictability and Return Predictability

## 3.1 The Conditional Flow-Performance Relationship

The Berk and Green (2004) model of rational fund flows assumes that investors are Bayesian and learn about managerial ability from a fund's past returns. In the equilibrium, rational investors adjust their capital flows based on past performance. Learning implies that fund flows should be positively related to past fund performance. We examine whether investors' flows react to past performance and whether the reaction to fund performance depends on market conditions.

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

$$\begin{aligned} Flow_{i,t+1} = \gamma_0 + \gamma_1^{Up} I(MKT_t = Up) + \gamma_1^{Down} I(MKT_t = Down) \\ + \gamma_2^{Up} I(MKT_t = Up) Performance_{i,t} + \gamma_2^{Down} I(MKT_t = Down) Performance_{i,t} \\ + \gamma_3 X_{i,t} + \epsilon_{i,t+1}, \quad (9) \end{aligned}$$

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 by both fund and by time. The coefficients of interest are the loadings on the interaction terms, $\gamma_2^z$ for $z \in \{Up, Down\}$.

The results, presented in Table 3, suggest a strong relation between fund flows and past performance. Moreover, the dependence of fund flows on past performance changes with 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 after down markets. The difference is statistically significant based on the F-test in the lower panel of the table.

## 3.2 Performance Predictability

The behavior of fund flows to performance offers a simple indication of differences in investors' learning across market conditions. But the fund flows by themselves are not sufficient to fully capture how efficiently investors' allocate their capital. 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 study the rationality of actual fund flows, we investigate if and when mutual fund investors leave money on the table. We check for the existence

[2] To control for potential nonlinearity effects we repeat the same analysis including squares of the fund-performance term and the results are robust to this change. The results are available upon request.

of predictability in mutual fund performance and compare it to the predictions from the Berk and Green (2004) model.

The Berk and Green (2004) model predicts that rational investors should 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 investors allocate 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 and sort observations based on the market condition during the next month. 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 are 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. But 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.[3] Past performance can be used to predict future fund performance after periods of high market returns, but not after periods of low market returns.

Can fund flows be used to predict future performance? How does the predictability depend on market conditions? We construct two equally weighted portfolios – the "High" portfolio includes

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

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 estimate a conditional version of the four-factor model used by Carhart (1997):

$$R_{j,t+1} = \alpha_j^0 + \alpha_j^{Up} I(MKT_t = Up) + \alpha_j^{Down} I(MKT_t = Down) + \sum_{k=1}^{K} \beta_{k,j} F_{k,t+1} + \epsilon_{j,t+1}. \qquad (10)$$

Table 4 reports the results. The table is divided into four sections, each corresponding to a different investment horizon. 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, we find no abnormal return from switching between low-flow and high-flow funds. But 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. 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.

[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.

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. Performance predictability is economically significant and, 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. We find similar results when we do not allow for conditional risk factors.

### 3.3 Robustness Checks

Although the results are suggestive of the important differences in performance predictability across market conditions, they may also be sensitive to our empirical design. We summarize the results of our robustness checks in Table 5. 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 sorting based on past one-month fund flows we sort based the average flows over the past three months using the median flow as our 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 Fama and French three-factor model; 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. While there is 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.

There is significant degree of predictability in the returns of a strategy in which investors switch capital between high-flow and low-flow funds after periods of high market returns, and no predictability in 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: Lynch and Musto (2003) document that investors' fund flows are sensitive to past raw returns. To allow for this possibility, 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 4 using raw returns.

The results using raw returns are qualitatively similar to those reported in Table 4. There is a significant degree of relative performance predictability after periods of high market returns but no relative performance predictability after periods of low market returns. Moreover, 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 magnitudes are comparable to that of strategies that condition on past fund flows. All the portfolio returns are statistically significant at the 1% level.

Finally, the predictability results might rely on differences between equally-weighted portfolios. By using equally-weighted portfolios in our tests, 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. We therefore 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 investors 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. The theoretical model's predictions allow us to interpret the inefficiency. It has been suggested that boundedly rational investors may overreact to information. Instead, 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.

# 4 Possible Explanations for the Empirical Results

## 4.1 Transaction Costs

The asymmetric inefficiencies we report could result from time-varying transaction costs. The 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 directly measure 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 (e.g., Bergstresser, Poterba, and Zarutskie (2003)). To this end, we test the tax story in two ways: Conditioning on funds' momentum loading, and conditioning on their turnover ratio. We 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 6 report the results for momentum-sorted portfolios. Consistent with the tax story, we find that the magnitude of the predictability is larger for the high-momentum portfolio. However, the patterns of performance predictability are qualitatively consistent with the previous findings for both low-momentum and high-momentum portfolios. We find statistically significant return predictability after up markets but not after down markets.

Similarly, Panels C and D of Table 6 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 larger for the high-turnover portfolio, but once again the difference between the two portfolios is economically negligible.

We conclude that our results are supportive of taxes effecting investors' behavior. But since the findings hold for both low momentum and low momentum portfolios and both low-turnover and high-turnover portfolios, our results are unlikely to be entirely driven by differences in transaction costs from capital gains taxation.

### 4.2 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 7 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.

### 4.3 Survivorship Bias

The design of our performance predictability tests requires 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 8 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.

### 4.4 Investors' Capital Allocation Mistakes

Here, we explore a behavioral explanation for our findings. We argue that the main mechanism behind our findings could be that some investors are more prone to making mistakes when allocating capital after periods of high market returns than after periods of low market returns. In particular, our results suggest that after periods of high market returns, mutual fund investors leave too much capital in poor performing funds and move too little capital into good performing funds.

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 estimate the specification used in equation (9) separately for the two groups of funds to test if the sensitivity of flows to performance varies between the two groups of funds.

Table 9 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 (10) separately for retail and institutional investors. Panel A of Table 10 presents the results for retail investors. We observe patterns similar to those presented in Table 4: strong predictability in the performance earned by switching capital across funds after up markets but no predictability in performance after down markets. The magnitude 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, such funds are also less known to investors, making it more likely for investors to make mistakes in their investments the funds. 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 11 reports the results.

We find a 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 significant for young funds, especially for short-term, one-month and three-month horizons, and are slightly weaker 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 tend 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.

# 5 Variations 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 efficiently, 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 more distinct cross-sectionally. 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 *Beta Deviation* 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:

$$BetaDeviation_{i,t} = \mid Beta_{i,t} - \overline{Beta}_{g,v} \mid . \tag{11}$$

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]

$$SectorDeviation_{i,t} = \frac{1}{J}(\sum_{j} \sqrt{\sum_{k} (w_{kj} - \overline{w}_{g,v})^2}), \tag{12}$$

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 Carhart (1997) four-factor model:

$$UnsystematicDeviation_{i,t} = \mid UnsystematicRisk_{i,t} - \overline{UnsystematicRisk}_{g,v} \mid . \tag{13}$$

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.

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

$$Dispersion_{i,t} = \lambda_0 + \lambda_1 I(MKT_t = Up) + \lambda_2 I(MKT_t = Down) + \lambda_3 X_{i,t} + FundF.E. + \epsilon_{i,t}. \tag{14}$$

[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, Sialmand Zheng (2005).

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 $\lambda_1$ and $\lambda_2$. 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, $\lambda_1$ will be negative and $\lambda_2$ will be positive.

The results, presented in Table 12, 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. In summary, the findings are consistent with the hypothesis that fund managers internalize the behavior of fund investors in their trading strategies.

## 6 Conclusion

Using a rational equilibrium model of mutual funds as a benchmark, we document that investors in the mutual fund sector do not always react efficiently to information and leave significantly more money on the table after periods of high market returns than they leave after periods of low market returns. Investing in a strategy that goes long in funds with high fund flows when market returns are high produces future abnormal returns, while investing in a strategy that goes long in funds with high fund flows when market returns are low does not produce future abnormal returns. Similarly, investing in a strategy that goes long in funds with good performance when market returns are high produces future abnormal returns, while investing in a strategy that goes long in funds with good performance when market returns are low does not produce future abnormal returns. The return 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.

We also document that the differential response in fund flows across market conditions is largely confined to flows into retail funds rather than flows into institutional funds, suggesting that the observed differences in returns result from differences in the behavior of retail investors. Fund managers seem to recognize tha investors behave differently in up and down markets, since managers adjust their strategies to the investors fund flows; their investment strategies are more dispersed cross-sectionally after periods of low market returns than after periods of high market returns.

Our results imply that the equity mutual fund industry is less efficient after high market returns when the industry size increases, than after low market returns. The 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 Thomson 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 (per 3m.)** | | **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 Carhart (1997) four-factor model. $I(MKT_t = Up)$ 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, per month | |
|---|---|---|
| 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: **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 %, per m.) | -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 %, per m.) | -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 %, per m.) | -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 5: **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 %, per m.) | 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 %, per m.) | -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 %, per m.) | -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 %, per m.) | -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 %, per m.) | 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 %, per m.) | -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 %, per m.) | -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 %, per m.) | -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 6: **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 %, per m.) | -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 %, per m.) | 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 %, per m.) | 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 %, per m.) | -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 %, per m.) | -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 %, per m.) | -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 %, per m.) | 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 %, per m.) | -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 7: **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 %, per m.) | -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 %, per m.) | -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 %, per m.) | 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 %, per m.) | -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 %, per m.) | -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 %, per m.) | -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 %, per m.) | 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 %, per m.) | -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 8: **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 %, per m.) | 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 %, per m.) | 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 9: **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, per month** | | | |
|---|---|---|---|---|
| | **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 10: **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 %, per m.) | 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 %, per m.) | -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 %, per m.) | -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 %, per m.) | -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 11: **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 %, per m.) | 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 %, per m.) | -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 %, per m.) | -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 %, per m.) | -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 12: **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.

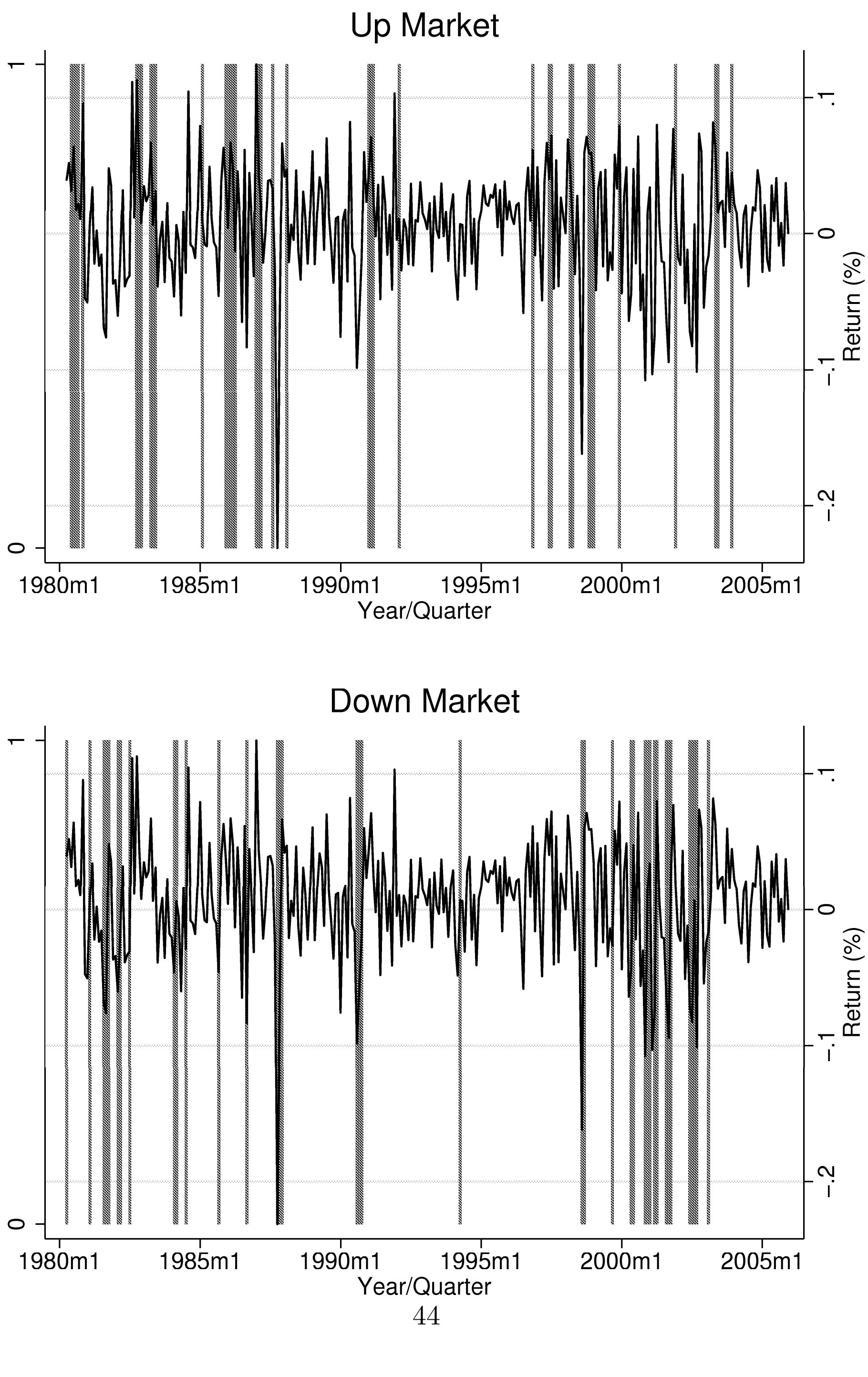

**Figure 2: Performance Persistence vs. Market Conditions**

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 worst (best) 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.