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

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Abstract

We provide novel evidence that mutual fund returns are predictable after periods of high market returns but not after periods of low market returns. The asymmetric conditional predictability in relative performance cannot be fully explained by time-varying differences in transaction costs, in style exposures, or in survival probabilities of funds. Performance predictability is more pronounced for funds catering to retail investors than for funds catering to institutional investors, suggesting that unsophisticated investors make systematic mistakes in their capital allocation decisions.

Mutual funds constitute one of the most important investment vehicles in the United States. 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.[1] In this paper, we ask how efficient are the choices mutual fund investors make across different market conditions. To do that, we look at the cross-sectional performance predictability of mutual funds and ask whether mutual fund investors can benefit by shifting from one subset of mutual funds to another.

A growing number of studies document the presence of skills among fund managers,[2] which leaves the capital-flow explanation relevant for understanding the predictability of fund returns. While the theoretical mechanism through which fund flows might eliminate performance predictability is well understood, empirical evidence on the efficiency of such flows is fairly sparse. Understanding the source and nature of capital allocation seems particularly relevant in the context of mutual funds, which are known to attract a wide spectrum of investors, not always well informed in their investment decisions. Whether capital flows eliminate mispricings in the cross section of fund returns is ultimately an empirical question.

Here, we shed new light on the efficiency of mutual fund investors' decisions by documenting the relationship between fund return predictability and fluctuations in the aggregate stock market. Anecdotal evidence and academic research suggest that swings in economic activity may be related to significant differences in investors' behavior, or composition. For example, the popular press has argued that the recent financial crisis brought about irrationally large downsizing of equity positions in the retirement accounts of retail investors, a fact commonly attributed to investors' overreaction in bad market conditions. Other studies find indirect evidence that unsophisticated investors are more likely to enter the stock

[1] See the 2009 Investment Company Factbook (http://www.icifactbook.org).

[2] See, Cohen, Coval, and Pástor (2005), Kacperczyk, Sialm, and Zheng (2005), and Kacperczyk and Seru (2007).

market when market returns are high.[3] That similar fluctuations in stock market conditions may also trigger mispricings in the mutual fund sector is worth investigating given the recent evidence of time-varying fund returns (see, e.g., Mamaysky, Spiegel, and Zhang (2007)).

We study how capital allocation decisions affect asset returns using a large sample of U.S. equity mutual funds over the 1980–2005 period. We examine the conditional cross-sectional predictability of mutual fund returns based on past performance and past flows. Fund performance is known as a useful measure when assessing the skill of a fund manager (see, e.g., Chevalier and Ellison (1999) and Berk and Green (2004)). We sort funds into past performance quintiles and track their subsequent performance. After periods of high market returns, subsequent portfolio rankings are 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, performance rankings change and the spread in four-factor alphas between high-performance 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.

Fund flows should proxy for investors' information about fund managers' skill and future performance. Funds that receive high capital flows in a given period should be funds for which investors have obtained good news and funds that receive low capital flows in a given period should be funds for which investors have obtained bad news. Building on empirical evidence (e.g., Gruber (1996) and Zheng (1999)) suggesting that funds with high past flows in a given month perform better than funds with low past flows, we separate funds into two groups: funds that received above-median flows, and funds that received below-median flows in that month. When we sort funds based on their past flows, instead of their past

[3] This evidence is documented in Grinblatt and Keloharju (2001), Lamont and Thaler (2003), Brunnermeier and Nagel (2004), and Cooper, Gutierrez, and Hameed (2004), among others. In addition, Seru, Shumway, and Stoffman (2010) show that unsophisticated investors learn more and make fewer mistakes in periods of low market returns.

performance, we find the same patterns in the cross-section of return predictability. After periods of high market returns the portfolio of high-flow funds earns 1.3% to 2.5% higher annualized abnormal return than the portfolio of low-flow funds. 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 are robust to the inclusion of momentum and liquidity factors, the use of time-varying factor loadings, and various definitions of market conditions and fund-flow cutoffs. Our results suggest that after high market returns, investors could increase their expected abnormal returns by moving their capital from funds with poor past performance and relatively low flows to funds with good past performance and relatively high flows.

We consider a number of explanations for our findings. First, fund investors may be subject to asymmetric trading frictions across 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 the degree of momentum tilt in a fund portfolio to proxy for the average effective capital gains tax liability, we find some support for the capital gains tax explanation, but it appears unlikely to fully explain our results.

Second, the observed patterns in performance predictability could be an artifact of the correlation 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 is high in up markets and zero in down markets, our results would attain. To explore such an alternative, we calculate the time-varying gains to predictability within various commonly used investment styles. We find evidence of performance predictability within each style category, suggesting 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 survivorship 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 less sophisticated investors. Comparing retail funds with institutional funds — one proxy for investors' sophistication—the asymmetry in predictability is largely concentrated among funds catering to retail investors. Further, the performance predictability is substantially stronger for young funds, consistent with the idea that young funds cater to less sophisticated investors. Such findings are consistent with the results in Bailey, Kumar, and Ng (2010) who show that more sophisticated investors earn on average higher returns on their mutual fund investments.

Given that after periods of high market returns the fund investors do not seem to process information as efficiently, fund managers' incentives to exert costly effort and acquire information in these states should be weaker. 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 fund managers' activeness is costly then it should rationally increase after periods of low market returns, responding to an increase in the fund flows' sophistication.

Our results are related to several strands of literature. First, the notion of predictability in mutual funds' performance is often simplified to the notion of performance persistence. The general finding of the literature is that fund performance does not persist on average, except for the worst performing funds (Carhart (1997)). This result is often interpreted as lack of persistence in managerial skills though this interpretation is largely driven by the measure of skill one uses.[4] We focus on the *time-series* patterns of persistence and show that the predictability varies with changes in stock market conditions.

Second, the paper is also related to studies showing that past flows can predict subsequent fund performance—the "smart money" effect. For example, Gruber (1996) and Zheng (1999) argue that fund flows tend to predict future fund performance. Wermers (2003) and Sapp and Tiwari (2004) cast doubt on the finding by showing that smart money is largely a momentum-driven phenomenon. Using the stock-level data based on mutual fund holdings, Frazzini and Lamont (2008) document that the smart-money effect is very short lasting. Instead, our view of the smart money effect is that smartly allocated money should eliminate any predictable differences in fund returns. We provide evidence that points to the importance of market conditions for evaluating the efficiency of fund flows.

Finally, our paper contributes to the literature that considers time-varying conditioning information in aggregate fund performance. Early contributions in this context build on the work by Ferson and Schadt (1996), which emphasizes the role of aggregate stock market predictors in the mutual fund performance evaluation. More recently, the focus has been directly on modeling differences in fund behavior across macroeconomic states. Glode (2011) 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. Pástor 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

[4] For example, recent studies find strong evidence of persistence in measures of skills that are based on the mix of holdings and return data (e.g., Kacperczyk and Seru (2007), Kacperczyk, Sialm, and Zheng (2008), Cremers and Petajisto (2009)).

industry. Compared to these studies, our work focuses on the cross-sectional properties 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.

The rest of the paper is as follows. In Section 1, we describe the basic economic mechanism that lays out the foundations for our empirical tests. In Section 2, we provide the discussion of the data. In Section 3, we present our main results on the conditional predictability in fund returns. Section 4 entertains a number of potential explanations for the predictability results. In Section 5, we examine the responses of fund managers to predictable variation in fund returns. Section 6 concludes.

1 Hypothesis Development

We use insights developed in the rational model of mutual fund investment of Berk and Green (2004) as the theoretical basis for our empirical tests. Although the predictions we derive are not specific to this model, we use it as a reference because it helps us conceptualize the main elements of our empirical framework.[5] In particular, it provides a useful benchmark of the empirical implications for rational mutual fund flows and how they relate to fund performance.

The main implication of the model we rely on for 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

[5] 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.

conditions should provide power in our empirical tests on the predictability of mutual fund performance.

In our empirical tests, we aim to identify situations in which the supply of investors' capital to mutual funds is such that excess returns adjusted for costs are predictable. For example, consider a situation in which a large number of investors participating in the mutual fund sector do not fully exploit emerging profit opportunities. Suppose that such investors were not responsive enough to information about past performance relative to a full-efficiency 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 such funds would offer a positive expected abnormal return. Similarly, funds with poor performance in one period would stay too big, their costs would be too large, and such funds would offer a negative expected abnormal return. 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 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 average of past market excess returns for this time period is higher than its historical 75th percentile. A market is *Mid* when the three-month average of past market excess returns for this time period is between its historical 25th percentile and 75th percentiles. A market is *Down* when the three-month average of past 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 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 *out-of-sample* percentiles from 1926 up to each observation date to proxy for the information investors had about market conditions at the time of their trading. Our results are robust to 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: 39 months are defined as up markets, 38 months are defined as down markets, and the remaining 232 months are defined as mid-markets. 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.

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 funds, bond funds, money market funds, international funds, sector funds, 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.

We use 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:

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

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 they do not necessarily have higher risk-adjusted performance after high market returns. 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 Evidence on Time-Varying Return Predictability

3.1 Performance Predictability

We test the hypothesis that fund investors move capital across funds in an attempt to benefit from future abnormal returns offered by some funds. The resulting capital flows should adjust fund size such that 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 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 (labelled $t = 0$), 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, subsequent alphas are not monotonically increasing in past alphas. 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.[6] Past performance can be used to predict future fund performance after periods of high market returns, but performance cannot be used to predict future performance after periods of low market returns.

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

Other pieces of information should be used by investors trying to make investment decisions. Unfortunately, we cannot observe all the information available, but we can observe fund flows and proxy for investors' information about fund managers' skill and future performance. For example, funds that receive high capital flows in a given period should be funds for which investors have obtained good news about future 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 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.[7] 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):

$$R_{j,t+1} = \alpha_j^0 + \alpha_j^{Up} I(MKT_t = Up) + \alpha_j^{Down} I(MKT_t = Down) + \sum_{k=1}^{K} \beta_{k,j} F_{k,t+1} + \epsilon_{j,t+1}. \quad (2)$$

Table 3 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 reports tests for the null that the the unconditional alphas of of the two portfolios are equal, and also tests for that the conditional alphas.

[7]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.

Unconditionally, we find no abnormal return from switching between low- 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, six, and 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.

The asymmetry is consistent with fund investors incorporating information more efficiently after periods of low market returns than after periods of high market returns, or equivalently with a less "sophisticated" mutual fund clientele after periods of high market returns than after periods of low market returns. After periods of low market returns, investors in a low-flow fund would not benefit from switching to a high-flow fund, but these investors would benefit from switching to a high-flow fund after periods of high market returns earning a significantly higher risk-adjusted return. Performance predictability is economically significant, with the magnitude of the spread decreasing 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.

3.2 Robustness Checks

We summarize the results of our robustness checks in Table 4. 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 on the average flows over the past three months using the median flow as a cut-off value. The results, though economically less significant, are qualitatively similar. We find statistically significant predictability after up markets but not after down markets. The results are similar if we use a six-month average flow instead. In Panel C, we condition the strategy on past-month percentage flows rather than on the dollar flows. Again, the results are similar qualitatively and the magnitudes are slightly larger than before.

Finally, in Panel D, we report abnormal returns calculated using the Fama and French three-factor model. The qualitative and the quantitative aspects of our results are similar for strategies after up markets when we use the three-factor model to define abnormal returns. There is statistically significant predictability after down markets, with the economic magnitudes of the spread portfolio becoming slightly larger. The result is consistent with evidence by Sapp and Tiwari (2004) that momentum is an important part of the observed unconditional predictability in mutual fund returns.

There is 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 fund past 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 using other predictive variables.

Another signal that investors might consider is past raw returns: Lynch and Musto (2003) show 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 two groups: a group with positive returns and a group with negative returns. We repeat the analysis in Table 3 using raw returns.

The results using raw returns are qualitatively similar to those reported in Table 3. 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 a strategy that conditions on past fund flows. All the portfolio returns are statistically significant at the 1% level.

Finally, the predictability results might be due to the use of equally weighted portfolios. By using equally weighted portfolios in our tests, we assign a greater weight to smaller funds. 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. The predictability results are therefore unlikely to be driven by differences between small and large funds.

The information in raw returns, in risk-adjusted returns, and in fund flows might be processed differently by investors after periods of high market returns than it is processed after periods of low market returns. Or equivalently, the investors trading mutual fund shares after periods of high market returns might process this information less diligently than the investors trading mutual fund shares after periods of low market returns. Overall, capital appears to be allocated more efficiently after periods of low market returns than after periods of high market returns. Boundedly rational investors might overreact to information, but our empirical evidence instead suggests that mutual fund investors under-react to information after periods of high market returns, and react appropriately after periods of low market returns. Funds with low past performance and low flows tend to remain too large after periods of high market returns, giving rise to subsequent abnormally low performance for up to a year.

4 Possible Explanations for the Empirical Results

We now entertain possible explanations for the time-varying predictability in fund returns. Our candidates include time-varying transaction costs, predictable variation in stock returns, differences in survivorship rates, and capital allocation mistakes.

4.1 Transaction Costs

Asymmetric predictability could result from time-varying transaction costs. The transaction costs would have to offset any abnormal gains unexplained by the common risk factors we use, implying that transaction costs are significantly higher after up markets than after down markets. We know of no evidence that direct trading costs or fund expenses change much over time, but transaction costs arising from 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 trading 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. We condition our tests on funds' momentum loadings and on funds' turnover ratios. 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 the two portfolios after up and down markets.

Panels A and B of Table 5 report the results for the momentum-sorted portfolios. Consistent with the tax story, we find that the magnitude of the predictability is larger for high-momentum funds than low-momentum funds. Still, the difference in alphas for high-flow and low-flow low-momentum funds is at least 1% on an annualized basis. The patterns of performance predictability are qualitatively consistent with our previously reported findings for both low-momentum and high-momentum portfolios of funds. There is statistically significant return predictability after up markets but not after down markets.

Similarly, Panels C and D of Table 5 report the results for portfolios of funds sorted by turnover ratios — above and below the sample median. There is strong performance predictability in both low-turnover and high-turnover portfolios of funds after up markets and no performance predicability after down markets. The economic magnitude of this phenomenon is only slightly larger for the high-turnover funds.

Our results are supportive of taxes affecting investors' behavior. But since the findings hold for both low-momentum and high-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

Perhaps the returns on our switching strategy occur because the strategy is correlated with some well-know passive strategies. For example, if high-flow funds were value funds and low-flow funds were growth funds, then switching between high-flow funds and low-flow funds would be the same as following a value strategy. To the extent that the profitability of the value strategy were high in up markets and zero in down markets, it would generate observationally equivalent results to ours. Although our empirical approach controls for any systematic differences in factor exposure, our adjustment may be imprecise. Hence, we examine the predictability results within different investment styles. Table 6 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 3; funds with *Value* indicator below 3 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 3; the funds with *Size* indicator above 3 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 may occur because our sample is tilted towards larger-cap funds, which might 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 Differences in Survivorship

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 be explained by 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 7 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, the asymmetric predictability in performance we document is unlikely to be driven by differences in funds' survivorship.

4.4 Investors' Capital Allocation Mistakes

One plausible mechanism behind our findings is that mutual fund investors – as a group – are more prone to making mistakes when allocating capital after periods of high market returns than after periods of low market returns. 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. 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 fund predictability to be more pronounced for retail investors than for institutional investors.

We estimate equation (2) separately for retail and institutional investors. Panel A of Table 8 presents the results for retail investors. We observe patterns similar to those presented in Table 3: 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 instrument we use is the fund age. Young funds may be regarded by investors as new and fashionable and so may attract fund 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 such funds. To this end, we consider two groups of funds: Funds that are not more than 3 years old, and funds that are 9 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 9 reports the results.

We find a significant degree of performance predictability in both groups of funds after up markets but not after down markets. The magnitude of the abnormal returns is quite different between the two groups. The abnormal returns are significant for young funds, especially for short-term, one-month and three-month horizons, and slightly weaker for longer horizons. The abnormal returns are significant only for old funds for the middle-term horizons. The results are consistent with the explanation that less sophisticated investors channel their funds extensively and quickly to new mutual funds and such investors 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 retail investors rather than institutional investors make more investment mistakes after up markets than after down markets.

5 Variations in Fund Managers' Strategies

Investors seem to incorporate information more efficiently after periods of low market returns than they do after periods of high market returns. Do fund managers respond to that by altering their behavior across market conditions? Following high market returns, fund managers should have weaker incentives to exert costly effort to acquire unique information, while following periods of low returns fund managers should have stronger incentives to exert effort. The type of information collected, processed, and used by mutual fund managers to form portfolios should vary with market conditions.

One way in which such time variation in incentives may show up is that when more unique information is known, funds should pursue investment strategies that are cross-sectionally more distinct. Here, 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 one, *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 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:

$$BetaDeviation_{i,t} = \mid Beta_{i,t} - \overline{Beta}_{g,v} \mid . \quad (3)$$

The second one, *Sector Deviation*, 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.[8]

$$SectorDeviation_{i,t} = \frac{1}{J}(\sum_j \sqrt{\sum_k (w_{kj} - \overline{w}_{g,v})^2}), \tag{4}$$

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 variable 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:

$$UnsystematicDeviation_{i,t} = \mid UnsystematicRisk_{i,t} - \overline{UnsystematicRisk}_{g,v} \mid . \tag{5}$$

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.

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

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

$$Dispersion_{i,t} = \lambda_0 + \lambda_1 I(MKT_t = Up) + \lambda_2 I(MKT_t = Down) + \lambda_3 X_{i,t} + Fund F.E. + \epsilon_{i,t}. \quad (6)$$

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

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

The results, presented in Table 10, show that fund 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 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. Fund managers appear to internalize the behavior of fund investors in their trading strategies.

6 Conclusion

We show some evidence of time-varying predictability in the cross section of mutual fund returns. Our evidence suggests 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 after periods of low market returns. Investing in funds with high fund flows when market returns are high produces future abnormal returns (compared with investing in funds with low fund flows), while investing similarly when market returns are low does not produce future abnormal returns. Similarly, investing in funds with good performance when market returns are high produces future abnormal returns (compared with investing in funds with poor performance), while investing in funds with good performance when market returns are low does not produce future abnormal returns. The return predictability is robust to the inclusion of standard risk and style controls, as well as the time-series variation in factor loadings.

The differential response in fund flows across market conditions is largely confined to retail funds, rather than institutional funds, consistent with the observed differences in returns result across these two groups of investors. Fund managers seem to recognize that investors behave differently in up and down markets — their investment strategies are more dispersed cross-sectionally after periods of low market returns than after periods of high market returns.

Our results suggest the presence of relative mispricings in the equity mutual fund industry after periods of high returns, exactly when industry size is large. The finding, in turn, has strong implications for mutual fund investors – mostly individual households – as well as for the overall market efficiency debate and asset pricing. Indeed, recent work by Vayanos and Woolley (2010) 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.

References

Bailey, Warren, Alok Kumar, and David Ng, Behavioral Biases of Mutual Fund Investors, 2010, *Journal of Financial Economics*, forthcoming.

Bergstresser, Daniel, James Poterba, and Rebecca Zarutskie, 2003, Mutual Fund Portfolio Turnover and the Effective Tax Burden on Taxable Investors, Working Paper, Duke University.

Berk, Jonathan B. and Richard C. Green, 2004, Mutual Fund Flows and Performance in Rational Markets, *Journal of Political Economy* **112**: 1269-1295.

Brown, Stephen, William Goetzmann, Jonnathan Ingersoll, and Stephen A. Ross, 1992, Survivorship Bias in Performance Studies, *Review of Financial Studies* **5**: 553-580.

Brunnermeier, Markus and Stefan Nagel, 2004, Hedge Funds and the Technology Bubble, *Journal of Finance* **59**: 2013-2040.

Carhart, Mark, 1997, On Persistence in Mutual Fund Performance', *Journal of Finance* **52**: 57-82.

Carpenter, Jennifer and Anthony W. Lynch, 1999, Survivorship Bias and Attrition Effects in Measures of Performance Persistence, *Journal of Financial Economics* **54**: 337-374.

Chen, Joseph, Harrison Hong, Ming Huang, and Jeffrey Kubik, 2004, Does Fund Size Erode Mutual Fund Performance?, *American Economic Review* **94**: 1276-1302.

Chevalier, Judith and Glenn Ellison, 1999, Career Concerns of Mutual Fund Managers, *Quarterly Journal of Economics* **114**: 389-432.

Christoffersen, Susan, 2001, Why do Money Fund Managers Voluntarily Waive their Fees?, *Journal of Finance* **56**: 1117-1140.

Cohen, Randolph, Joshua D. Coval, and Ľuboš Pástor, 2005, Judging Fund Managers by the Company that They Keep, *Journal of Finance* **60**: 1057-1096.

Cooper, Michael J., Roberto C. Gutierrez, and Allaudeen Hameed, 2004, Market States and Momentum, *Journal of Finance* **59**: 1345-1366.

Cremers, Martijn and Antti Petajisto, 2008, How Active is Your Fund Manager? A New Measure that Predicts Performance, *Review of Financial Studies* **22**: 3329-3365.

Edelen, Roger M., Richard Evans, and Gregory B. Kadlec, 2007, Scale Effects in Mutual Fund Performance: The Role of Trading Costs, Working Paper, University of Virginia.

Elton, Edwin J., Martin J. Gruber, and Christopher R. Blake, 2001, A First Look at the Accuracy of CRSP Mutual Fund Database and a Comparison of the CRSP and the Morningstar Mutual Fund Database, *Journal of Finance* **56**: 2415-2430.

Fama, Eugene F. and Kenneth R. French, 1997, Industry Costs of Equity, *Journal of Financial Economics* **43**: 153-193.

Ferson, Wayne E. and Rudi W. Schadt, 1996, Measuring Fund Strategy and Performance in Changing Economic Conditions, *Journal of Finance* **51**: 425-461.

Frazzini, Andrea and Owen A. Lamont, 2008, Dumb Money: Mutual Fund Flows and the Cross-Section of Stock Returns, *Journal of Financial Economics* **88**: 299-322.

Glode, Vincent, Why do Mutual Funds 'Underperform'?, *Journal of Financial Economics* **99**: 546-559.

Grinblatt, Mark and Matti Keloharju, 2001, What Makes Investors Trade?, *Journal of Finance* **56**: 589-616.

Gruber, Martin. J., 1996, Another Puzzle: The Growth in Actively Managed Mutual Funds, *Journal of Finance* **51**: 783-810.

Kacperczyk, Marcin and Amit Seru, 2007, Fund Manager Use of Public Information: New Evidence on Managerial Skills, *Journal of Finance* **62**: 485-528.

Kacperczyk, Marcin, Clemens Sialm and Lu Zheng, 2005, On the Industry Concentration of Actively Managed Equity Mutual Funds, *Journal of Finance* **60**: 1983-2011.

Kacperczyk, Marcin, Clemens Sialm and Lu Zheng, 2008, Unobserved Actions of Mutual Funds, *Review of Financial Studies* **21**: 2379-2416.

Kacperczyk, Marcin, Stijn van Nieuwerburgh, and Laura Veldkamp, 2010, Rational Attention Allocation over the Business Cycle, 2010, Working Paper, New York University.

Lamont, Owen A. and Richard H. Thaler, 2003, Can the Market Add and Subtract? Mispricing in Tech Stock Carve-Outs, *Journal of Political Economy* **111**: 227-268.

Lynch, Anthony W. and David K. Musto, 2003, How Investors Interpret Past Returns, *Journal of Finance* **58**: 2033-2058.

Mamaysky, Harry, Matthew Spiegel, and Hong Zhang, 2007, Estimating the Dynamics of Mutual Fund Alphas and Betas, *Review of Financial Studies* **21**: 233-264.

Newey, Whitney K. and Kenneth D. West , 1987, A Simple Positive-Definite Heteroskedasticity and Autocorrelation Consistent Covariance Matrix, *Econometrica* **55**: 703-708.

Pástor, Ľuboš and Robert Stambaugh, 2010, On the Size of the Active Management Industry, Working Paper, University of Chicago and University of Pennsylvania.

Sapp, Travis and Ashish Tiwari, 2004, Does Stock Return Momentum Explain the "Smart Money" Effect?, *Journal of Finance* **54**: 2605-2622.

Seru, Amit, Tyler Shumway, and Noah Stoffman, 2010, Learning by Trading, *Review of Financial Studies*, **23**: 705-739.

Vayanos, Dimitri, and Paul Woolley, 2010, Fund Flows and Asset Prices: A Baseline Model, Working Paper, London School of Economics.

Wermers, Russell, 2000, Mutual Fund Performance: An Empirical Decomposition into Stock-Picking Talent, Style, Transactions Costs, and Expenses, *Journal of Finance* **55**: 1655-1703.

Wermers, Russell, 2003, Is Money Really 'Smart'? New Evidence on the Relation between Mutual Fund Flows, Manager Behavior, and Performance Persistence, Working Paper, University of Maryland.

Zheng, Lu, 1999, Is Money Smart? A Study of Mutual Fund Investors' Fund Selection Ability, *Journal of Finance* **54**: 901-933.

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 average of past market excess return is higher than the 75th percentile of the historical three-month average of past market excess returns (starting Q3 of 1926); and zero otherwise. $I(MKT_t = Mid)$ equals one when the three-month average of past market excess return is between the 25th and 75th percentiles of the historical three-month average of past market excess returns (starting Q3 of 1926); and zero otherwise. $I(MKT_t = Down)$ equals one when the three-month average of past market excess return is lower than the 25th percentile of the historical three-month average of past market excess 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 average of past market excess return is higher than the 75th percentile of the historical three-month average of past market excess returns (starting Q3 of 1926); and zero otherwise. $I(MKT_t = Mid)$ equals one when the three-month average of past market excess return is between the 25th and 75th percentiles of the historical three-month average of past market excess returns (starting Q3 of 1926); and zero otherwise. $I(MKT_t = Down)$ equals one when the three-month average of past market excess return is lower than the 25th percentile of the historical three-month average of past market excess 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: **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 average of past market excess return is higher than the 75th percentile of the historical three-month average of past market excess returns (starting Q3 of 1926); and zero otherwise. $I(MKT_t = Mid)$ equals one when the three-month average of past market excess return is between the 25th and 75th percentiles of the historical three-month average of past market excess returns (starting Q3 of 1926); and zero otherwise. $I(MKT_t = Down)$ equals one when the three-month average of past market excess return is lower than the 25th percentile of the historical three-month average of past market excess 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 4: **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 average of past market excess return is higher than the 75th percentile of the historical three-month average of past market excess returns (starting Q3 of 1926); and zero otherwise. $I(MKT_t = Mid)$ equals one when the three-month average of past market excess return is between the 25th and 75th percentiles of the historical three-month average of past market excess returns (starting Q3 of 1926); and zero otherwise. $I(MKT_t = Down)$ equals one when the three-month average of past market excess return is lower than the 25th percentile of the historical three-month average of past market excess 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 5: **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 average of past market excess return is higher than the 75th percentile of the historical three-month average of past market excess returns (starting Q3 of 1926); and zero otherwise. $I(MKT_t = Mid)$ equals one when the three-month average of past market excess return is between the 25th and 75th percentiles of the historical three-month average of past market excess returns (starting Q3 of 1926); and zero otherwise. $I(MKT_t = Down)$ equals one when the three-month average of past market excess return is lower than the 25th percentile of the historical three-month average of past market excess 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 6: **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 average of past market excess return is higher than the 75th percentile of the historical three-month average of past market excess returns (starting Q3 of 1926); and zero otherwise. $I(MKT_t = Mid)$ equals one when the three-month average of past market excess return is between the 25th and 75th percentiles of the historical three-month average of past market excess returns (starting Q3 of 1926); and zero otherwise. $I(MKT_t = Down)$ equals one when the three-month average of past market excess return is lower than the 25th percentile of the historical three-month average of past market excess 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 7: **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 average of past market excess return is higher than the 75th percentile of the historical three-month average of past market excess returns (starting Q3 of 1926); and zero otherwise. $I(MKT_t = Mid)$ equals one when the three-month average of past market excess return is between the 25th and 75th percentiles of the historical three-month average of past market excess returns (starting Q3 of 1926); and zero otherwise. $I(MKT_t = Down)$ equals one when the three-month average of past market excess return is lower than the 25th percentile of the historical three-month average of past market excess 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 8: **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 average of past market excess return is higher than the 75th percentile of the historical three-month average of past market excess returns (starting Q3 of 1926); and zero otherwise. $I(MKT_t = Mid)$ equals one when the three-month average of past market excess return is between the 25th and 75th percentiles of the historical three-month average of past market excess returns (starting Q3 of 1926); and zero otherwise. $I(MKT_t = Down)$ equals one when the three-month average of past market excess return is lower than the 25th percentile of the historical three-month average of past market excess 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 9: **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 average of past market excess return is higher than the 75th percentile of the historical three-month average of past market excess returns (starting Q3 of 1926); and zero otherwise. $I(MKT_t = Mid)$ equals one when the three-month average of past market excess return is between the 25th and 75th percentiles of the historical three-month average of past market excess returns (starting Q3 of 1926); and zero otherwise. $I(MKT_t = Down)$ equals one when the three-month average of past market excess return is lower than the 25th percentile of the historical three-month average of past market excess 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 10: **Fund Strategies and Market Conditions**

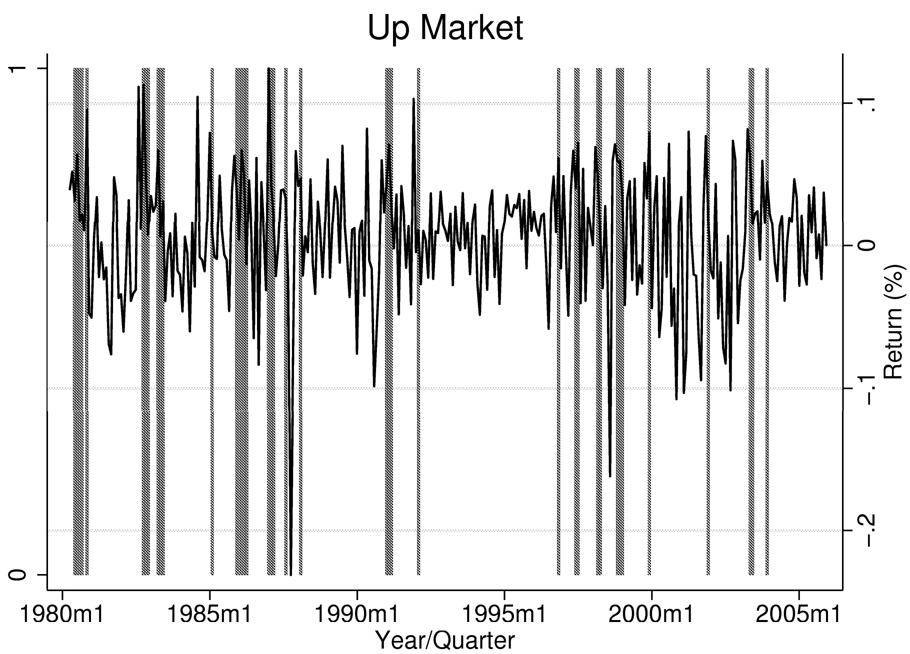
The dependent variables are *BetaDeviation* in Columns (1) and (2), *SectorDeviation* in Columns (3) and (4) and *UnsystematicDeviation* in Columns (5) and (6). Bottom row provides the F-test along with its p-values of the differences between coefficients on $I(MKT_t = Up)$ and $I(MKT_t = Down)$. Our 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 average of past market excess return is higher than the 75th percentile of the historical three-month average of past market excess returns (starting Q3 of 1926); and zero otherwise. $I(MKT_t = Mid)$ equals one when the three-month average of past market excess return is between the 25th and 75th percentiles of the historical three-month average of past market excess returns (starting Q3 of 1926); and zero otherwise. $I(MKT_t = Down)$ equals one when the three-month average of past market excess return is lower than the 25th percentile of the historical three-month average of past market excess 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 average excess returns is higher than the 75th percentile of the historical three-month 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 average excess returns is lower than the 25th percentile of the historical market excess return. The data cover the period 1980 to 2005.



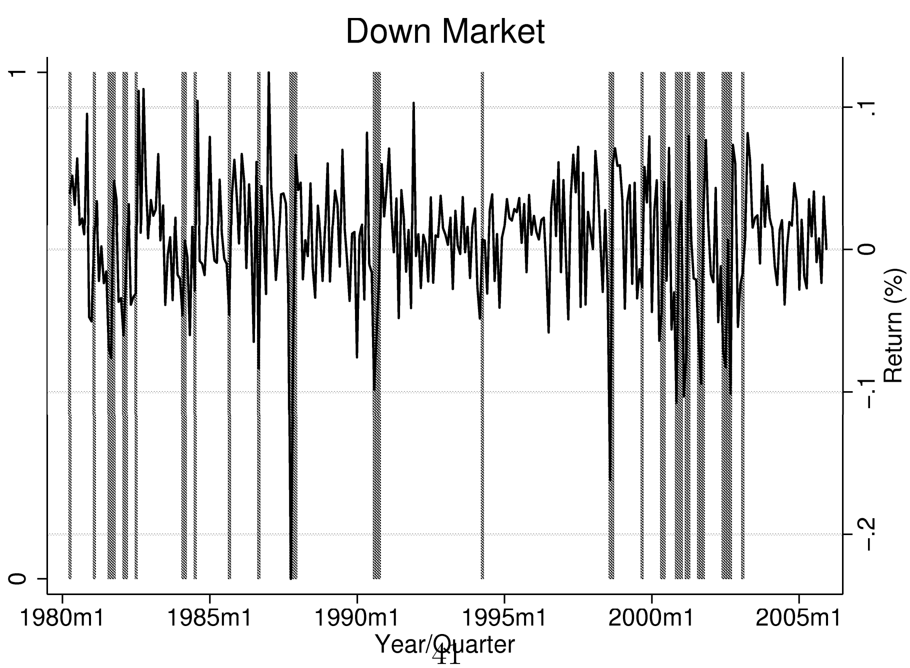


Figure 2: Performance Persistence vs. Market Conditions

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 average excess returns is higher than the 75th percentile of the historical three-month 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 average excess returns is lower than the 25th percentile of the historical market excess return. The data cover the period 1980 to 2005.