Time Variation in Information Production: Evidence from Mutual Funds

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Abstract

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We investigate the time variation in information production in the context of U.S. actively managed mutual funds. We show that investment strategies of funds are more dispersed when market returns are low. Further, investors respond differently to fund performance depending on market conditions. Fund flows are less sensitive to past performance in down markets than in up markets. At the same time, in down markets investors learn about funds from other sources, in that fund flows are more responsive to information contained in other sources, such as funds' investment strategies. We argue that the differences in flow sensitivity can be driven by time variation in information production.

JEL classification: G23, G11, G14.

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I. Introduction

Is the production of information time varying? Previous studies argue that the quality of information may change with market conditions. Dyck and Zingales (2003) claim that less unique private information is generated in up markets since "incentives to uncover information by speculators are much smaller during stock market booms". Also, Welch (2000) finds that analysts produce less unique information when market conditions are favorable. And Campbell, Lettau, Malkiel, and Xu (2001) document that stock market volatility tends to increase after a drop in market prices.

We investigate the time variation in information production in the mutual fund industry. Actively managed mutual funds are a natural market to study the use of information since their very existence depends on the production and use of financial information. Empirically, we document that fund managers' strategies change with market conditions. Mutual fund flows react to information, such as the mutual funds' abnormal performance. We document how investors react to information in different market conditions by showing how the flow of funds differ across market conditions.

We use quarterly data on more than 3,000 unique U.S. diversified equity funds over the period 1980-2005. Funds' investment strategies are more dispersed when market returns are low than when market returns are high; the cross-sectional deviations in terms of systematic risk, unsystematic risk, and industry concentration are larger when market returns are low.

We also look at the relationship between fund flows and past fund performance. The question is motivated by empirical evidence in a number of studies that document that funds with good abnormal performance tend to receive higher flows than funds with poor abnormal performance.[1] Empirically, little is known about how fund-specific flows react to information contained in fund performance in different market conditions. We find that

[1] See, for example, Chevalier and Ellison (1997), Sirri and Tufano (1998), and Del Guercio and Tkac (2002).

investors respond differently to fund performance in different market conditions. Although we observe a positive relation between flows and performance in all market conditions, fund flows are less sensitive to past performance in down markets than in up markets.

But are investors' reactions to information justified by the information content of fund abnormal performance? In order to determine whether the reactions are justified by the information content of performance we use the arguments in Berk and Green (2004) as our rational benchmark for how investors flows should react to new information. In the Berk and Green (2004) model, investors rationally funnel flows based on their estimate of managerial ability. Managerial ability is assumed to exhibit decreasing returns to scale. In equilibrium, money flows until the expected abnormal performance of each fund is zero. As a consequence, the model predicts that the flows should be such that there is no performance persistence. Empirically, we compare performance persistence in down and up markets. We find little evidence of performance persistence when market returns are low, but some persistence when returns are high. These patterns suggest that differences in flows, when conditioning on market returns, are driven by time variation in the information available to mutual fund investors.

Are investors able to learn about managerial ability in down markets through other signals besides performance? Moreover, since we do find some persistence in performance in up markets, can we observe that investors use information more efficiently when market returns are low relative to when market returns are high? We choose managerial investing strategies as signals of managerial ability that investors could learn from. We conjecture that investors might learn more efficiently in down markets by putting more weight on these signals relative to the weight they put in up markets. Consistent with our conjecture we find that investors are more responsive to information about investment strategies in down markets than they are in up markets.

An extensive empirical literature examines the performance of mutual funds based on either factor models or fund holdings. Studies based on factor-based measures include Jensen (1968), Malkiel (1995), Gruber (1996), Ferson and Schadt (1996), and Carhart (1997). Holding-based measures are considered by Grinblatt and Titman (1993), Grinblatt, Titman, and Wermers (1995), Daniel, Grinblatt, Titman, and Wermers (1997), Chen, Jegadeesh, and Wermers (2000), and Kacperczyk, Sialm, and Zheng (2005a). More recent studies, including Păstor and Stambaugh (2002), Cohen, Coval, and Păstor (2005), Cremers and Petajisto (2007), Kacperczyk and Seru (2007), and Kacperczyk, Sialm, and Zheng (2007) consider measures that factor in beliefs and different ways of measuring information content.

Empirical evidence on the persistence of mutual fund performance is mixed. Brown and Goetzmann (1995) and Elton, Gruber, and Blake (1996), among others, find statistical evidence of performance persistence for U.S. mutual funds. Carhart (1997) finds that the Jegadeesh and Titman (1993) momentum factor can explain in large part the year-to-year persistence observed when using performance measures not accounting for momentum. More recently, Kosowski, Timmermann, White, and Wermers (2006) use recursive portfolios sorted annually on past four-factor alphas (including a momentum factor) to study performance persistence. They find that an equal-weighted recursive portfolio of funds that were in the top decile in terms of alphas in the previous year generate a future alpha close to 1% in the next year. They also find that deciles 6 to 10 generate significantly negative alphas in the future.

Remolona, Kleiman, and Gruenstein (1997) study how market returns influence aggregate mutual fund flows. They find that the positive effect of market-wide returns on aggregate fund flows is weak, at best. But interestingly, they find that the relationship becomes stronger during certain episodes of major market declines, i.e. fund flows decrease during major market declines. Also see Warther (1995), Edelen and Warner (2001), and Karceski (2002) who study the inverse relationship: the effect of aggregate fund flows on market-wide returns. Further, Moskowitz (2000) finds that, although average mutual fund returns are unconditionally lower than market-wide returns, mutual fund returns are greater than market-wide returns during recessions. Kosowski (2006) uses risk-adjusted performance measure and finds significant over-performance during recessions, but not during the remainder of the business cycle.

II. Model

Suppose a one-period economy where the state $s \in S$ is known. A representative investor has marginal utility m_s in state s. The current framework does not require a parameterization of the pricing kernel m_s. The only assumption made on m_s is that it is higher in bad states than in good states, similar to what a consumption-based model parameterization would predict.

The investor can exert effort $e_s^I \in \Re^+$ in state s to learn more about different fund managers (skills, strategies, etc.). The more he learns about the fund managers, the better the investor can pick those who will outperform. For simplicity, I assume that the abnormal performance allowed by effort e_s^I is simply e_s^I. This abnormal performance is collected at the end of the period.

Learning about fund managers and generating an abnormal performance of e_s^I costs $C(e_s^I)$ at the beginning of the period. The cost function $C : \Re^+ \to \Re^+$ is increasing and strictly convex in effort. The costs may be seen as research expenses or as opportunity costs for the investor's time. The cost function is assumed to be independent of the state of the economy.

In state s, the investor faces the following optimization problem:

$$\max_{e_s^I} \; m_s e_s^I - C(e_s^I). \tag{1}$$

In each state, the optimal effort e_s^{I*} satisfies $m_s = C'(e_s^{I*})$. The strict convexity of $C(\cdot)$ implies that the optimal effort level e_s^{I*} increases with the pricing kernel m_s. Hence in bad economic states, when m_s is higher, investors will spend more effort to research mutual funds. Therefore Berk and Green's (2004) prediction is more likely to hold during bad times, as is the case in our sample.

Now suppose that the compensation (fee, flows, career, etc.) that a fund manager receives for his own effort e_s^M increases with the investor's knowledge of the industry, as represented by the investor's effort e_s^I. When the investor is well informed, managerial effort should be compensated more than when the investor is uninformed. Let $V(e_s^I)e_s^M$ be the reward collected by a fund manager who exerts effort e_s^M when the representative investor exerts effort e_s^I. The function $V(\cdot)$ is assumed to be positive and strictly increasing. Similar to the investor, the fund manager faces a cost function $K(e_s^M)$ when he exerts effort e_s^M. In our model, the cost function $K(\cdot)$ carries all the information useful to identify the skill level of a fund manager. If one manager faces larger costs than another in order to produce e_s^M, he is therefore less skilled than the other. We assume that this cost function takes the quadratic form $K(x) = \frac{\theta}{2}x^2$, for $x \geq 0$, where $\theta > 0$. Therefore $K'(x) = \theta x$ and θ is the slope of the marginal cost function. As θ increases, the cost of producing active returns increases as well. The skill level of the fund manager is symbolized by θ^{-1}.

Therefore, he faces the following optimization problem:

$$\max_{e_s^M} \; V(e_s^I)e_s^M - \frac{\theta}{2}(e_s^M)^2, \tag{2}$$

for a given level of effort e_s^I by the investor.

The FOC's in each state leads to $V(e_s^I) = \theta e_s^{M*}$, i.e. the marginal cost of effort equals the marginal reward collected because of this effort. Thus, as the investor exerts more effort to pick the best fund managers, the effort exerted by the fund manager increases as well.

Therefore, in equilibrium, we should observe higher effort from the investor in bad states and this should also lead to higher effort from the fund manager. Both of these predictions can be linked to our empirical findings.

III. Data and Summary Statistics

For our empirical analysis, we merge the CRSP Survivorship Bias Free Mutual Fund Database with the Thompson Financial CDA/Spectrum holdings database and the CRSP stock price data following the methodology of Kacperczyk, Sialm, and Zheng (2007). Our sample covers the time period between 1980 and 2005. The CRSP mutual fund database includes information on fund returns, total net assets, different types of fees, investment objectives, and other fund characteristics. The CDA/Spectrum database provides stock–holdings of mutual funds. These data are collected both from reports filed by mutual funds with the SEC and from voluntary reports generated by the funds. We also link reported stock–holdings to the CRSP stock database.

We focus our analysis on open-end domestic diversified equity mutual funds, for which the holdings data are most complete and reliable. We therefore eliminate balanced, bond, money market, international, sector, and index funds, as well as funds not invested primarily in equity securities from our sample. We also exclude funds which hold less than 10 stocks, those which invest less than 80% of their assets in equity, those which in the previous month manage less than 5 million and those which have an annual expense ratio above 4%. For funds with multiple share classes, we eliminate the duplicate funds and compute the fund-level variables by aggregating across the different share classes. Appendix A provides further details on the sample selection.

Table 1 reports summary statistics of the main fund attributes. Our sample includes 3,261 distinct funds and 81,971 fund-quarter observations. The number of funds in each quarter ranges from 158 (1980, Q2) to 1,636 (2001, Q4). We report summary statistics on fund total net assets (TNA), age, expenses, monthly returns, monthly performance, based on a four-factor model, and new money growth. We define new money growth (NMG) as the growth rate of the assets under management (TNA) after adjusting for the appreciation of the mutual fund's assets (R_t^i), assuming that all the cash flows are invested at the end of the period.

$$NMG_t^i = \frac{TNA_t^i - TNA_{t-1}^i * (1 + R_t^i)}{TNA_{t-1}^i} \tag{3}$$

As Elton, Gruber, and Blake (2001) report, the CRSP mutual fund databse contains errors associated with mutual fund mergers and splits. These errors result in extreme values of NMG_t^i. To reduce the impact of such outliers, we replace extreme values (i.e. top and bottom 0.5%) by the 99.5 and 0.5 percentile values respectively.

We use a three-quarter moving-average of market returns to proxy for market conditions. Market return is defined as $MKT_t = \sum_{\tau=t-2}^{t} \frac{R_\tau^{mkt}}{3}$, where R_τ^{mkt} denotes the S&P500 return during quarter τ. We capture the level of the conditioning variable in each quarter by assigning it into one of three categories: *High*, *Low*, and *Mid* such that 20% of the quarters with the highest levels of the conditioning variable are assigned into the first category, 20% of the quarters with the lowest levels of the conditioning variable are assigned into the second category, and the remaining quarters are assigned into the third category. Accordingly, we define two indicator variables I(π_t = Up) and I(π_t = Down) to capture the state of the market. $I(\pi_t = \text{Up})$ equals to one if the conditioning variable is in the top 20%, and zero otherwise; I(π_t = Down) equals to one if the conditioning variable is in the bottom 20%, and zero otherwise.

IV. Mutual Fund Investment Strategies

We argue that the amount of information produced by mutual funds may vary with market conditions. Thus, one would expect that in times with more unique information being produced, funds may want to pursue more distinct investment strategies. We explore such a possibility by analyzing how dispersion in investment strategies across funds changes with market conditions. To capture the degree of dispersion in fund managers' investment decisions, we use three measures of dispersion in portfolios held by managers, similar to Chevalier and Ellison (1999). These measures capture dispersion in managers' portfolios with respect to a typical portfolio at a given time t. We now discuss these measures.

IV.A. Dispersion Measures

We consider three dispersion measures. The first dispersion measure is $SectorDeviation_{it}$, which measures boldness in the style of the manager. It captures how much a manager concentrates his portfolio in sectors that differ from those that are most popular at the time. Specifically, $SectorDeviation_{it}$ 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).[2]

$$SectorDeviation_{it} = \frac{1}{J}(\sum_{j}\sqrt{\sum_{k}(w_{kj} - \overline{w}_{g,v})^2}), \tag{4}$$

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.

[2]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 (2005b).

The second dispersion measure is $UnsysDeviation_{it}$ and 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, $UnsysRisk_{it}$, and the sample average of this variable over all funds in fund i's objective class in quarter t. $UnsysRisk_{it}$ is the absolute value of the residual from the four-factor model of Carhart (1997).

$$UnsysDeviation_{it} = \mid UnsysRisk_{it} - \overline{UnsysRisk}_{g,v} \mid \tag{5}$$

Finally, the third dispersion measure is $BetaDeviation_{it}$. It measures boldness in the sense of taking a large bet on the direction of the market. The variable is calculated as the absolute value of the difference between fund i's beta in quarter t and the average beta in that quarter of all funds in fund i's objective class. Individual fund beta is a market beta from a four-factor model calculated using 36 months of past returns.

$$BetaDeviation_{it} = \mid Beta_{it} - \overline{Beta}_{g,v} \mid \tag{6}$$

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

IV.B. Empirical Results

Our tests relate the measures of dispersion of investment strategies to market conditions using a multivariate regression framework. Specifically, we estimate the regression model:

$$Dispersion_{i,t} = \beta_0 + \beta_1 I(\pi_t = \text{Up}) + \beta_2 I(\pi_t = \text{Down}) + \beta_3 X_{i,t} + TimeFE + \epsilon_{i,t}. \tag{7}$$

Here $Dispersion_{i,t}$ denotes the degree of similarity in investment strategy of fund i at time t and is proxied by *SectorDeviation*, *UnsysDeviation*, and *BetaDeviation.* $\mathrm{I}(\pi_t = \mathrm{Up})$ and $\mathrm{I}(\pi_t = \mathrm{Down})$ represent the state of the market and $X_{i,t}$ defines the set of different control variables. Our other controls include fund size, fund past flows, and fund age. We additionally include time fixed effects in all our specifications. Finally, some of the specifications include fund fixed-effects.

The coefficients of interest are β_1 and β_2. We expect these coefficients to systematically vary if the fund strategies differ in up and down markets. For instance, if the fund manager strategies are similar in up markets relative to down markets, we should expect β_1 to be negative and/or β_2 to be positive.

We present the results of this regression in Table 2 using the three measures of managerial investment strategies. The first, third and fifth columns of the table report the results using a random fund effects specification. We find that the funds exhibit more similarity in terms of *BetaDeviation* ($\beta_1 < 0$) and *UnsysDeviation* ($\beta_2 > 0$). The results are mixed for *SectorDeviation* where we find that $\beta_2 > 0$ and $\beta_1 > 0$ as well. The second, fourth, and sixth columns report the results of re-estimating the regression model including fund fixed effects. Doing so controls for any time-invariant fund characteristics. The results suggest that $\beta_1 < 0$ for *BetaDeviation*, and $\beta_2 > 0$ for *UnsysDeviation* and *SectorDeviation.* These results strongly support the notion that the portfolio characteristics of funds are more similar in the up market relative to down market.

V. The Flow-Performance Relationship

Given that fund managers follow investment strategies that are time varying, it is reasonable to expect that investors' reaction to fund performance is also time varying. We examine how the relationship between past performance and subsequent fund flows changes with market conditions. Our hypothesis suggests that flows and their sensitivity to fund performance should differ with market conditions.

Since the flow-performance relationship has been shown to be nonlinear (see Chevalier and Ellison (1997)), we start by depicting the flow-performance relation semi-parametrically. Since flows may be also affected by fund characteristics other than performance, we first remove the variation in flows that is caused by these other conditioning variables. To this end, we estimate the pooled regression:

$$NMG_{t+1}^{i} = a + b_1 Age_t^i + b_2 Ln(TNA_t^i) + b_3 Exp_t^i + TimeFE + e_t^i, \tag{8}$$

where Age_t^i denotes the number of years elapsed, as of time t, since fund i was first offered; $Ln(TNA_t^i)$ denotes the log of total net assets, in millions of dollars, of fund i at time t; Exp_t^i denotes the percentage total fees charged annually by fund i at time t, and $TimeFE$ captures time fixed-effects. Note that time fixed-effects account for overall flows in and out of the actively managed equity mutual fund industry.

We look at the flows not explained by fund characteristics, as defined by e_t^i in equation (8), which we refer to as *unexplained flows*, and relate them to past fund performance. At the end of each quarter, we group funds into 20 equal-size bins based on funds' four-factor alphas during that quarter. We then separate the bins depending on whether they were formed during up or down market and average the flows within each bin. Figure 1 reports the results.

Overall, there is a positive association between performance and subsequent flows, both in up and down markets and flows seem to be less sensitive to past performance in down markets. The pattern holds both for well and poor performing funds. Also, the shape of the flow-performance relationship seems somewhat different in up and down markets; it appears more convex in up markets than in down markets.

These observations are further corroborated by a more parametric regression analysis. To capture both market dependency and possible non-linearities in the flow-performance relation in the regressions, we interact dummy variables for the three levels of the market condition with fund flows and squared fund flows.[3]

We estimate the regression:

$$NMG^i_{t+1} = \beta_0 + \beta_1\pi_t + \beta_2\pi_t\alpha^i_t + \beta_3\pi_t(\alpha^i_t)^2 + \beta_4 X^i_t + TimeFE + \epsilon^i_t, \tag{9}$$

where π_t is the market state variable at time t ($\mathrm{I}(\pi_t = \mathrm{Up})$ or $\mathrm{I}(\pi_t = \mathrm{Down})$) are indicator variables for market returns; α^i_t is fund i's four-factor alpha in quarter t, and $X_{i,t}$ defines the set of control variables including fund size, expenses, and fund age. We also include time fixed effects. To facilitate interpretation of the results, we standardize all fund characteristics by demeaning each variable by its sample standard deviation.

Table 3 reports the estimation results. The regression results reported in the third column 3 are consistent previous studies that suggest a strong and convex relation between past fund performance and subsequent flows. For example, a fund with an alpha of 1% should experience a flow of roughly 0.5% more than an identical fund with an alpha of 0%.

The conditional regressions reported in the second and fourth columns suggest a strong dependence of flows on market conditions. The coefficient on α^i_t goes down by roughly 50% in down markets, compared to up markets (reported in the second column). The finding suggests that flows respond less to a given level of realized alpha in down markets than in up markets.

From the results reported in the fourth column, fund flows seem somewhat more convex in down markets relative to up markets, although the difference is not statistically significant.

[3]We repeat the same analysis including a cubic fund performance term, which we do not report here. The results are largely unaffected.

Overall, we find that past performance is an important determinant of subsequent fund flows. Further, we show that the flow-performance relationship strongly depends on market conditions. When market returns are low, flows appear to be less sensitive to past performance.

VI. Performance Persistence

Flows react differently to performance depending on market conditions. The question is whether investors' reactions to information is justified by the information content of fund abnormal performance. We link the changes in the flow-performance relationship to changes in the informational environment. According to Berk and Green (2004), rational flows would ensure that expected alpha is zero across all funds. Fund performance therefore should have no persistence. We use the prediction as a way of evaluating whether changes in flow-performance sensitivity are rational responses to changes in the informational environment.

To test performance persistence we follow Carhart (1997). We assign funds into decile portfolios based on their past performance. The funds are then sorted based on the state of the market in this quarter. Subsequently, we calculate the average alpha of each portfolio over the subsequent one quarter.

Figure 2 depicts the results. We observe significantly different persistence patterns depending on whether portfolios were formed in up or down markets. In up markets, next quarter alphas are monotonically related to past alphas. The difference in next quarter alphas between deciles 1 and 10 is 0.89% per quarter. In contrast, in down markets subsequent alphas of these portfolios do not have any significant relation past performance. All performance deciles exhibit negative alpha of -0.5% to -1.0%.

In summary, we find that the lower sensitivity of flows to performance in bad markets does not result in more performance persistence. Therefore, the patterns we document suggest that differences in flows, when conditioning on market returns, are driven by the time variation in the informational environment.

VII. The Flow-Performance Relation and Investment Strategies

We found that fund flows are less sensitive to performance in down markets than in up markets. At the same time, lack of response by investors does not lead to any persistence in fund performance in the down market. An obvious question therefore is whether investors are able to learn about managerial ability in down markets through other signals besides performance? Moreover, since we do find some persistence in performance in up markets, do investors use information more efficiently in up markets relative to low markets? Following our results in Section IV., we choose managerial investing strategies (*SectorDeviation*, *UnsysDeviation*, and *BetaDeviation*) as signals of managerial ability that investors could learn from. We hypothesize that investors might learn more efficiently in down markets by putting more weight on managerial strategies relative to the weight they put on the strategies in up markets.

We add variables that control for changes in managerial investing strategies to the regressions in (9). The results are presented in Table 4. The first three columns of the table report the results from including each of the investment strategy variables in turn, and the fourth column reports the results from including all the measures together. The fifth column also include fund fixed effects to control for any time invariant fund specific traits that might drive investor flows.

Our results in all the specifications suggest that investors put more weight on the strategies in down markets. In other words, fund flows are more sensitive to these measures in down markets than in up markets. For robustness, we also examine whether investor response to other fund specific variables (like age of the fund) also varies with market conditions. We find no such evidence.

Overall, our findings suggest that investors are using information about investment strategies differently depending market conditions. More specifically, investors seem to assign more weight to investment strategies of managers in down markets. This may explain why investors are able to respond to fund performance in a more rational manner–in the Berk and Green (2004) sense by competing away performance persistence–when the market conditions are down.

VIII. Conclusion

We show that mutual fund managers as well as their investors behave differently depending on market conditions. In particular, investment strategies are more dispersed when market returns are low than when they are high. We also find that investors respond differently to fund performance and fund investment strategies depending on market conditions. Using the Berk and Green's (2004) economy as a benchmark, we argue that the difference in flow sensitivity may be driven by time variation in information production.

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Appendix A. Sample Selection

We start with a sample of all mutual funds in the CRSP mutual fund database covering the period between 1980 and 2005. The focus of our analysis is on domestic equity mutual funds, for which the holdings data are the most complete and reliable. As a result, we eliminate balanced, bond, money market, sector, and international funds, as well as funds not invested primarily in equity securities.

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 and those which have an annual expense ratio above 4%.

Elton, Gruber, and Blake (2001) and Evans (2004) 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. Data may be reported prior to the year of fund 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. Data may be reported prior to the year of fund organization if a fund is incubated before it is made publicly available, and these funds might not report their names or some other fund attributes, as shown by Evans (2004). Incubated funds also tend to be smaller, which motivates us to exclude funds that had in the previous month less than $5 million in assets under management.

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

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

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

Table 1: **Summary Statistics**

This table presents summary statistics for our sample of equity mutual funds over the period 1980 to 2005. Statistics for all market conditions, up markets only and down markets only are presented.

	Conditions	**Mean**	**S.D.**	**Median**	**p25**	**p75**
Size ($M) (TNA)	All	941.1529	3699.2923	159.6960	47.2000	559.7890
	Up only	853.9363	3335.2786	152.3560	48.0220	529.9000
	Down only	894.0135	3371.6658	148.7805	42.4790	524.0000
Annual Expense Ratio (Exp)	All	0.0128	0.0048	0.0123	0.0097	0.0154
	Up only	0.0123	0.0047	0.0117	0.0093	0.0150
	Down only	0.0131	0.0048	0.0125	0.0099	0.0158
Fund Flow (NMG)	All	0.1055	0.5646	0.0018	-0.0335	0.0697
	Up only	0.1443	1.0587	0.0114	-0.0287	0.0946
	Down only	0.0571	0.2287	-0.0039	-0.0329	0.0465
Raw Return	All	0.0263	0.1045	0.0313	-0.0226	0.0868
	Up only	0.0874	0.0690	0.0958	0.0454	0.1328
	Down only	-0.0584	0.1196	-0.0439	-0.1519	0.0369
Alpha (4-factor)	All	-0.0035	0.0392	-0.0032	-0.0215	0.0147
	Up only	-0.0056	0.0346	-0.0040	-0.0229	0.0131
	Down only	-0.0069	0.0486	-0.0044	-0.0297	0.0176
Age (years)	All	13.0157	14.2268	8.0000	4.0000	16.0000
	Up only	13.4933	14.7721	8.0000	3.0000	17.0000
	Down only	12.8701	13.8701	8.0000	4.0000	16.0000

Table 2: **Fund Strategies Conditional on Market Returns**

The dependent variable is *BetaDeviation* in Columns (1) and (2), *SectorDeviation* in Columns (3) and (4) and *UnsystematicDeviation* in Columns (5) and (6). *BetaDeviation* is calculated as the absolute value of the difference between fund i's beta in quarter t and the average beta in that quarter of all funds in fund i's objective class. Individual fund beta is a market beta from a four-factor model calculated using 36 months of past returns. *SectorDeviation* 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). *UnsystematicDeviation* is calculated as the absolute value of the difference between a fund's unsystematic risk, $UnsysRisk_{it}$, and the sample average of this variable over all funds in fund i's objective class in quarter t. $UnsysRisk_{it}$ is the absolute value of the residual from the four-factor model of Carhart (1997). $\mathrm{I}(\pi_t = \mathrm{Up})$ is an indicator variable equal to one if the market is up and zero otherwise; $\mathrm{I}(\pi_t = \mathrm{Down})$ is an indicator variable equal to one if the market is down and zero otherwise. Our controls include fund age, a natural logarithm of fund assets, and new money growth defined as a growth in fund assets over time. The data covers the period 1980 to 2005. Standard errors have been included in parentheses. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.

	Beta Deviation		Sector Deviation		Unsys Deviation	
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathrm{I}(\pi_t = \mathrm{Up})$	-.013	-.023	.014	.011	-.019	-.015
	(.007)**	(.009)***	(.006)**	(.007)	(.058)	(.025)
$\mathrm{I}(\pi_t = \mathrm{Down})$	.002	-.005	.015	.016	.041	.099
	(.010)	(.009)	(.006)**	(.006)***	(.024)*	(.025)***
Age	-.0005	-.0003	-.0002	-.001	-.0007	-.004
	(.0001)***	(.0002)**	(.0002)	(.0004)***	(.0004)*	(.0006)***
Log(Assets)	-.002	-.001	-.006	-.003	.007	.014
	(.0005)***	(.0005)***	(.001)***	(.001)***	(.002)***	(.002)***
NMG	.003	.003	-.008	-.012	.012	.011
	(.001)***	(.0009)***	(.002)***	(.002)***	(.005)**	(.004)***
Observations	66,791	66,791	66,791	66,791	66,791	66,791
R^2	.062	.074	.054	.061	.071	.105
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Random Fund Fixed Effects	Yes		Yes		Yes	
Fund Fixed Effects		Yes		Yes		Yes

Table 3: **Flow-Performance Relationship Conditional on Market Returns**
The dependent variable is the subsequent fund flow as defined in equation 3. I(π_t = Up) is an indicator variable equal to one if the market is up and zero otherwise; I(π_t = Down) is an indicator variable equal to one if the market is down and zero otherwise. Performance is computed using Carhart's (1997) 4-factor model. Our controls include fund age, a natural logarithm of fund assets, and time-fixed effects. The data covers the period 1980 to 2005. Standard errors have been included in parentheses. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.

	Subs. Flow	Subs. Flow	Subs. Flow	Subs. Flow
Performance	0.51	0.645	0.512	0.635
	(0.047)***	(0.071)***	(0.047)***	(0.069)***
Age	-0.011	-0.011	-0.011	-0.011
	(0.001)***	(0.001)***	(0.001)***	(0.001)***
Log(TNA)	0.002	0.002	0.002	0.002
	(0.001)	(0.001)	(0.001)*	(0.001)
Expenses	0.004	0.003	0.003	0.003
	(0.001)**	(0.001)**	(0.001)**	(0.001)**
Dummy(High)		-0.089		-0.064
x Performance		(0.100)		(0.106)
Dummy(Low)		-0.361		-0.32
x Performance		(0.080)***		(0.086)***
Performance Sq.			0.888	0.432
			(0.372)**	(0.617)
Dummy(High)				0.361
x Performance Sq.				(0.948)
Dummy(Low)				0.436
x Performance Sq.				(0.734)
Constant	0.018	0.018	0.016	0.017
	(0.000)***	(0.000)***	(0.001)***	(0.001)***
Observations	61924	61924	61924	61924
R^2	0.04	0.04	0.04	0.04
Time Fixed Effects	Yes	Yes	Yes	Yes

Table 4: **Flow-Performance Relationship, Market Conditions, and Managerial Strategies**

The dependent variable is the subsequent fund flow as defined in equation 3. $I(\pi_t = \text{Up})$ is an indicator variable equal to one if the market is up and zero otherwise; $I(\pi_t = \text{Down})$ is an indicator variable equal to one if the market is down and zero otherwise. Fund investment strategy variables are as described in Table 2. Performance is computed using a four-factor model of Carhart's (1997). Controls variables not shown in the table due to space considerations include fund age, a natural logarithm of fund assets, expenses and any other variables included in Table 3. The data covers the period 1980 to 2005. Standard errors have been included in parentheses. ***, **, and * denote significance at 1%, 5% and 10% levels, respectively.

	Subsequent Flow				
	(1)	(2)	(3)	(4)	(5)
$I(\pi_t = \text{Down})$ x BetaDeviation	.044 (.012)***			.047 (.012)***	.050 (.012)***
$I(\pi_t = \text{Up})$ x BetaDeviation	-.004 (.016)			.005 (.016)	.005 (.016)
$I(\pi_t = \text{Down})$ x UnsysDeviation		.002 (.004)		-.0007 (.004)	-.0001 (.004)
$I(\pi_t = \text{Up})$ x UnsysDeviation		-.012 (.004)***		-.012 (.004)***	-.012 (.004)***
$I(\pi_t = \text{Down})$ x SectorDeviation			.011 (.006)**	.012 (.006)**	.012 (.006)**
$I(\pi_t = \text{Up})$ x SectorDeviation			-.014 (.007)**	-.012 (.007)*	-.012 (.007)*
BetaDeviation	-.018 (.008)**			-.024 (.008)***	-.018 (.009)**
UnsysDeviation		.014 (.002)***		.015 (.002)***	.018 (.002)***
SectorDeviation			.002 (.003)	.0008 (.003)	.0002 (.003)
Performance	.550 (.021)***	.548 (.021)***	.551 (.021)***	.547 (.021)***	.503 (.021)***
Performance Sq.	.424 (.181)**	.327 (.180)*	.387 (.181)**	.369 (.181)**	.463 (.183)**
$I(\pi_t = \text{Down})$ x Performance	-.312 (.034)***	-.303 (.034)***	-.314 (.034)***	-.304 (.034)***	-.302 (.034)***
$I(\pi_t = \text{Up})$ x Performance	-.083 (.049)*	-.078 (.049)	-.080 (.049)	-.078 (.049)	-.087 (.049)*
$I(\pi_t = \text{Down})$ x Performance Sq	.376 (.258)	.475 (.258)*	.467 (.257)*	.345 (.260)	.199 (.261)
$I(\pi_t = \text{Up})$ x Performance Sq	.314 (.517)	.495 (.518)	.325 (.514)	.539 (.521)	.474 (.523)
$I(\pi_t = \text{Up})$	-.031 (.017)*	-.019 (.017)	-.018 (.017)	-.016 (.017)	-.029 (.017)*
$I(\pi_t = \text{Down})$	-.007 (.017)	.005 (.017)	.003 (.017)	.019 (.016)	.004 (.016)
Observations	64,455	64,455	64,455	64,455	64,455
R^2	.034	.033	.034	.041	.054
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes
Fund Random Effects	Yes	Yes	Yes	Yes	
Fund Fixed Effects					Yes

Figure 1: Fund-Performance Relationship Conditional on Market Returns
The graph plots the unexplained flows, as defined by $e_{t,i}$ in equation 8, for each of our twenty groups. All funds are grouped, every quarter, into 20 equal-sized bins based on their four-factor alpha performance during that quarter. "High" identifies the relationship observed when the market was up during the previous quarter; "Low" identifies the relationship observed when the market was down during the previous quarter.

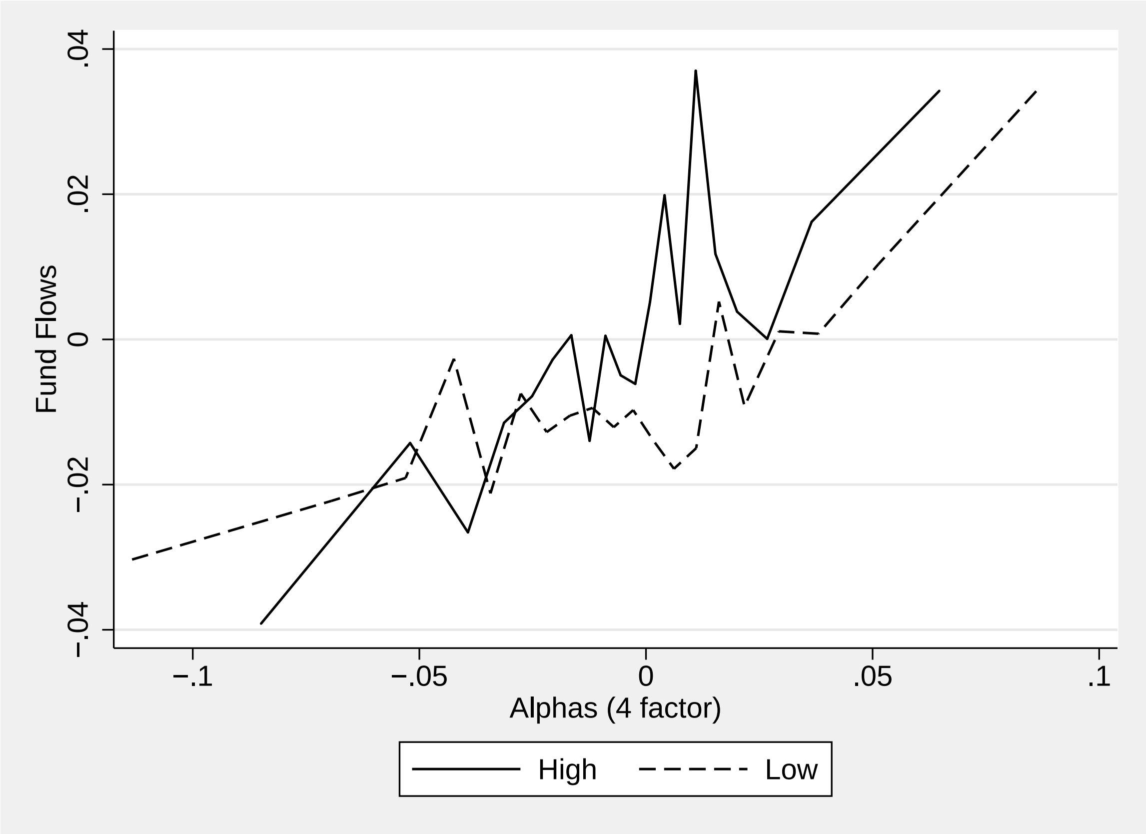

Figure 2: Quarterly Performance Persistence Conditional on Market Returns

This graph plots the four-factor alpha on 10 equal-weighted portfolios based on the deciles associated with past performance. "High" identifies the relationship observed when the market was up during the previous quarter; "Low" identifies the relationship observed when the market was down during the previous quarter.