Measures of Downside Risk and Mutual Fund Flows*

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Abstract

Mutual funds that recently outperformed receive a disproportionate share of new money, despite no clear evidence that good performance persists. In this paper I examine whether consumers also use past performance to identify funds with lower downside risk. I explore the response of fund flows to performance in declining markets compared to the performance in up markets. Estimates of up and down-market betas as well as down and up-market alphas are obtained from mutual funds' performance conditioned on the sign of the market's excess returns. Consumers invest more heavily in funds that recently produced higher relative down-market alpha and higher relative up-market beta. Fund flows react in a similar way to another proxy of down-market risk based on conditional absolute returns. The results of this research confirm that mutual fund investors seek portfolio insurance, in addition to performance.

Keywords: **downside risk, mutual fund, fund flows.**

JEL Classification: D8, G11

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1 Introduction

Mutual funds are very popular among American households. By the end of 2007, individual investors owned nearly 92% of the $6.5 trillion in assets managed by open-end equity funds[1]. Academics and money managers spend effort trying to understand how investors select funds out of a vast list of available managers. The empirical evidence suggests that fund flows follow managers with high returns or high alpha. A few studies have also focused on funds with superior market timing[2] . Market timers provide two benefits for investors: increase risk adjusted returns and, more importantly, trim down large losses when the market declines. In this paper I examine if investors also chase funds with lower downside risk in addition to those with good performance. In this framework funds with low downside risk are the ones with high down-market alpha and low down-market beta. For robustness I propose a similar measure derived directly from returns that captures low downside risk. In both approaches I find that fund flows do follow funds with low downside risk.

The downside risk literature examines the role of assets that mitigate losses at times when investor's wealth drops. These portfolios are quite important at times when other assets tend to have higher cross correlations. However, it is not clear that investors have an ability to identify true market timers using recent history. Nevertheless, the empirical evidence confirms that investors chase assets that have displayed those characteristics in the past.

Ang, Chen, and Xing (2006) work with down-market beta to study downside risk in the equity market. They find that stocks with high downside beta outperform stocks with lower downside beta, a result which is attributed exclusively to downside conditional beta, not unconditional beta. In another paper, Ang and Chen (2002) also found that correlations between U.S. stocks and the aggregate U.S. market are far greater for downside moves than for up moves. Together, these results suggest that investors recognize and properly price the nonlinearities in asset returns. In particular, they demand a premium to hold securities that perform poorly in declining markets.

Likewise, assets that perform well in declining markets provide valuable diversification at times

[1]Source - 2008 Investment Company Institute (ICI) Factbook.

[2]A fund with superior market timing is one that has higher up-market beta than down-market market beta. However, a nonconstant beta may in fact be associated with spurious timing (Jagannathan and Korajczyk 1985).

when other assets are highly correlated. Equity mutual funds' returns also display asymmetries and may be affected by investor's attitude towards these nonlinearities. While stocks react through price, mutual funds have two layers: portfolio holdings and the net inflows of capital. In particular, I examine if equity funds that attenuate losses from market declines attract more capital than other funds with similar unconditional performance, but unfavorable payoffs in down-markets. Risk aversion implies that a dollar paid when market declines is worth more than a dollar paid when the market goes up[3]. This suggests that investors care whether managers produce down-market alpha, in addition to unconditional alpha and timing.

Treynor and Mazuy (1966) propose a technique to assess a fund manager's ability to forecast market-wide events. Henriksson and Merton (1981) construct another test to detect and measure timing by breaking up return into positive and negative parts, and then estimating dichotomous betas. Jagannathan and Korajczyk (1986) show that a portfolio that invests in options may produce spurious market timing. In particular, artificial timing is achieved at the cost of lower alpha. In this paper, I do not distinguish true from spurious timing ability. I focus, instead, on the response of flows to funds with low down-market beta. The demand for alpha is associated with the slope of the representative agent's money metric utility while the demand for timing is related to the curvature of the money metric utility. As a result alpha is expected to have a first order effect on the flow of funds while timing should have a second order effect. So the net effect will depend on the relative magnitudes of each of those proxies. Thus, I ignore the distinction between true and spurious timing and simply focus on the partial effects of flows in response to alpha and to measures of downside risk protection.

The literature on fund flows show that investors base their mutual fund purchasing decisions on recent performance. Ippolito (1992), Goetzman and Peles (1997), and Sirri and Tufano (1998) find a positive nonlinear relation of flows to performance indicating that investors allocate disproportionately more money into the extreme top performers. In fact, the flows to the extreme bottom performers are almost insensitive to performance. Management fees are usually paid as a fixed percentage of assets under management. Therefore, the convex performance-flow relationship creates an option-like payoff scheme for manager's compensation. This performance-flow shape provides managers an incentive to deviate from their goal of maximizing risk adjusted expected returns.

[3]For more details see Appendix A

Instead, their motivation is to make the top of the performance charts. This is consistent with the evidence provided by Chevalier and Ellison (1997), who find that funds alter the riskiness of their portfolios during the course of the year. Other papers also find that fund's with high market timing ability also attract mutual fund investment.

Finance professionals frequently debate whether actively managed equity funds add value for investors, and how they do so. This question has been addressed in different ways, and produces controversy among academics and practitioners. The early work by Jensen (1968) and more recently Malkiel (1995) and Gruber (1996) reveal that fund managers do not have superior stock-picking ability. Other studies including Grinblatt and Titman (1992), Hendricks, Patel, and Zeckhauser (1993), Wermers (1996), and Bollen and Busse (2005) find evidence that mutual fund performance persists in the short-run, suggesting that a significant portion of managers display some sort of trading talent. Other authors, like Malkiel (1995), Carhart (1997), and Wermers (2000), dismiss this evidence by stating that persistence in the data is a result of survivorship bias and benchmark misspecification.

Amidst this controversy, the study by Staal (2005) provides evidence that mutual funds deliver when it matters most to investors. By considering time-varying risk exposures (betas) and measure of superior ability (alpha) he finds that actively managed funds perform well in times when investors' income is low. This conclusion provides a new perspective on active management, suggesting that those funds represent a valuable investment option for households and institutional investors, even if on average funds underperform the benchmark.

The empirical evidence I provide shows that mutual funds that perform well in declining markets receive more net inflows than those funds with similar unconditional performance that perform well in appreciating markets. This is consistent with the prediction that payoffs delivered when the market declines are more valuable than payoffs delivered when the market goes up. These findings reinforce the belief that investors seek portfolio insurance, in addition to performance. More importantly, they rely on recent performance to select funds with lower downside risk.

The rest of the paper is organized as follows: Section 2 describes the database, section 3 introduces the different ways to measure fund performance, section 4 shows how to measure fund flows and sets up the empirical experiment, section 5 provides a few summary statistics and illustrates the term structure of fund flows, section 6 delivers the main empirical tests and results, section 7 addresses the performance persistence, and section 8 concludes.

2 Data

The mutual fund sample in this study is drawn from the CRSP U.S. mutual fund database, which is survivor-bias free [4]. The frequency at which variables are reported varies throughout the period covered in the database. For this paper, I use the CRSP files which contain quarterly and monthly data for all U.S. open-end mutual funds that operated at any point between December 1969 and March 2007. The main variables extracted from CRSP include:

1. *Total net assets* (TNA), represents the total dollar value of assets under management by each mutual fund, reported at the quarterly frequency.

2. *Total return*, represents the return on assets under management, net of fees and expenses, and accounts for reinvestment of all distributions. However, it disregard loads and other exit fees, as well as taxes. Return is reported at the monthly frequency.

3. *Objective* category is based on the Weisenberger and ICDI objective variables.

4. *Fund Name* is also used to help narrow down the sample of mutual funds.

I filter the selection of funds to focus on US domestic, actively managed, equity funds that belong to four different investment styles. Each fund is assigned to an investment style based on Pástor and Stambaugh's (2002) classification. The four styles considered are aggressive growth, growth, income, and growth-and- income[5]. Funds not in one of these categories are disregarded. In addition to Weisenberger and ICDI variables, a mutual fund's name is used to exclude from the sample non-equity funds, index funds, sector funds, real estate funds, life cycle funds, and international funds. The details of this filtering procedure are spelled out in the appendix[6].

The number of actively managed equity mutual funds grew significantly through the years and peaked in March of 2002 when there were a total of 3,389 funds. That is significantly higher than

[4] However, CRSP is not startup-bias free.

[5] Weisenberger objective code variable is denoted by OBJ and ICDI objective code variable is denoted by ICDI_OBJ_CD. Pastor and Stambaugh's (2002) classifications for the four styles that I consider in ths paper are chosen according to the following rule: Aggressive growth funds if OBJ is denoted MCG or AGG, and if ICDI_OBJ_CD is denoted by AG or AGG; Growth funds if OBJ is denoted G, S-G, G-S, GRO, or LTG, and if ICDI_OBJ_CD is denoted by LG; Income funds if OBJ is denoted I, I-S, IEQ, or ING, and if ICDI_OBJ_CD is denoted by IN; Growth and Income funds if OBJ is denoted GCI, I-G, G-I, G-I-S, G-S-I, I-G-S, I-S-G, S-G-I, S-I-G, or GRI, and if ICDI_OBJ_CD is denoted by GI. The identical procedure can be found on p. 18 of Staal (2005).

[6] The name-implied styles based on a mutual fund's name do not often reflect the true investment styles based on its portfolio (see Cooper, Gulen, Rau (2005)). However, sector's and non-equity funds are often identified by the fund's name.

the 188 funds operating in 1974. The mutual fund sample covers a total of 5,150 funds and 167,911 fund-quarters. Table 1 provides additional statistics to help give a sense of the evolution of the fund industry throughout the sample period.

The amount of assets under management also grew with the number of funds. In the cross section, however, one can observe the persistent right skewness in the size of funds. It reveals that large funds are disproportionately large, in comparison to the smaller funds. This feature has been observed consistently throughout the sample period.

(Insert table 1)

The return on CRSP's value weighted market index and the return of the one month T-bill rate are obtained from prof. Ken French's website[7]. The one month T-bill rate is used as proxy for the risk free rate. The difference between the market return and the risk-free rate is the measure for the market's excess return.

With the collected data I estimate conditional and unconditional performance measures for each mutual fund. In the next section I provide further details on the estimation procedure for each of these quantities. I also use the available data to estimate fund flows. The constructed database with fund flows and the performance measures provide the key inputs for the empirical analysis carried out in the rest of the paper.

3 Conditional Mutual Fund Performance

I obtain the timing and source of fund performance from conditional and unconditional return equations. These quantities are derived from a modified one factor specification, which captures a fund's upside and downside exposure to the market. For robustness, I derive analogous estimates directly from raw returns instead of regressions.

3.1 Modified One Factor Model

Instead of regressing a fund's return on the market, I regress it on two modified market return variables. The first variable is equal to the market's excess return when the market return is higher than the risk free rate and 0 otherwise. The second variable is equal to the market's excess

[7] I thank Prof. Ken French for providing CRSP market return and the risk free rate information on his website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

return when the return is lower than the risk-free rate and 0 otherwise. These variables identify a fund's upside and downside exposure to the market. (The rolling window for each quarter covers the previous twenty four months of monthly returns. In this modified one-factor model the dichotomous decomposition of market return requires enough months with positive and negative returns to guarantee accurate parameter estimation). The regression captures the co-movement of a fund with the market in an asymmetric fashion and provides different loading on the state in which the market beats the risk free rate compared to the state in which the market underperforms the risk-free rate.

Let the asset return generating process be defined as a filtered probability space $(\Omega, \mathcal{A}_t, P)$. In each period t, let $D_t = \{\omega \in \Omega : R_t^m(\omega) \leq 0\}$ and $U_t = \{\omega \in \Omega : R_t^m(\omega) > 0\}$ denote the event that market's excess return is negative and the event that market's excess return is positive respectively, where R_t^m is the market's excess return at t. In other words, D_t and U_t represent the events in which the market declines and appreciates, respectively. Also, let $r_t^+ = \max[0, R_t^m]$, and $r_t^- = \min[0, R_t^m]$.

The modified one-factor specification is given by the unconditional regression

$$R_{i,t} = \breve{\alpha}_{i,t} + \breve{\beta}_{i,t}^{+} r_t^+ + \breve{\beta}_{i,t}^{-} r_t^- + \varepsilon_{i,t}, \qquad (1)$$

where $R_{i,t}$ is the mutual fund i's excess return at time t.

Equation (1) splits the market's upward and downward moves through r_t^+ and r_t^- and provides a more flexible framework than Jensen's (1968) one factor model. As a result, $\breve{\alpha}$ which measures a fund's risk-adjusted abnormal return differs from Jensen's α due to the distinction between up and down market moves. In the presence of timing the biases from market timing and downside risk are embedded in Jensen's alpha. However, in equation (1) those biases are eliminated and $\breve{\alpha}$ provides a refined measure of a manager's stock picking skill. Henriksson and Merton (1981) used equation (1)[8] to detect market timing, but Jagannathan and Korajczyk (1986) show that their method may capture spurious market timing. The objective of this paper is to study investor's attitudes towards the downside and upside risk that they perceive in mutual funds. Therefore, by assuming that individual investors are unsophisticated there is no need to focus on issues related to robust measurement of true market timing.

In order to distinguish the contribution of alpha from downside and upside market moves, I can

[8]Equation (1) is identical to equation (28) in Henriksson and Merton (1981).

separately estimate two conditional one factor regressions; one to capture the upside moves and another one to capture the downside moves. In these specifications the conditioning event is the sign of the market's excess return. (As in the unconditional regression, the rolling windows cover twenty four months of data.) The conditional regressions, are estimated from the equations:

$$R_{i,t}|_{U_t} = \alpha_i^+ + \beta_i^+ R_t^m|_{U_t} + \varepsilon_{i,t}^+, \tag{2}$$

$$R_{i,t}|_{D_t} = \alpha_i^- + \beta_i^- R_t^m|_{D_t} + \varepsilon_{i,t}^-, \tag{3}$$

where $R_{i,t}$ |. is the mutual fund's excess return, conditional on the sign of the market's excess return, R_t^m |. is the market's excess return, conditional on the sign of the market's excess return. The measure of downside risk β_i^- was introduced by Bawa and Lindenberg (1977) and more recently used by Ang, Chen, Xing (2006). However, Ang et al use a different threshold for the up and down events. They use the average market return as the cutoff instead of the risk-free rate. Both of these levels make sense, but I chose the risk-free rate since returns below the risk-free rate are a more clear indication of a bear market than simply underperforming the average market return.

Expressions $\alpha^-(\alpha^+)$ in equations (2) and (3) represent a modified measure of risk-adjusted performance relative to the market, conditional on the market going down (up). These expressions identify if mutual funds have delivered alpha in bear market, in a bull market, or in both.

Briefly summarizing: $\breve{\alpha}_i$ measures the unconditional risk-adjusted performance of funds, while $\alpha_i^-(\alpha_i^+)$ measures the performance of a fund when the market is down(up). In addition, if $\breve{\beta}_i^+ \approx \beta_i^+$ and $\breve{\beta}_i^- \approx \beta_i^-$ then I relate the alphas by $\breve{\alpha}_i \approx p\alpha_i^+ + (1-p)\alpha_i^-$, where $p = P(U_t)$. This relation may not hold, in general, due in part to the positive covariance between r_t^+ and r_t^- and because the conditional (co)variances are not equal to the corresponding unconditional (co)variances[9]. Nevertheless, by setting $\breve{\alpha}_i \approx p\alpha_i^+ + (1-p)\alpha_i^-$ as an approximation, I obtain a direct link between unconditional and conditional performance[10]. Furthermore, equation (1) provides an effective unconditional model to identify a fund's performance when the market moves up and when it moves down. Therefore, I shall use this as the benchmark to measure overall abnormal performance.

[9] For more details see the appendix.

[10] In the sample I cannot reject that $\breve{\alpha} = p\alpha^+ + (1-p)\alpha^-$.

3.2 Conditional Return-Based Measures

In this section I introduce return-based conditional measures, to express the mutual fund's excess return conditional on the sign of market's return. One of the measures captures how much of the fund's return occurred when the market went up while the other measure captures how much of the fund's return occurred when the market went down, without identifying whether those returns were achieved from manager's ability (alpha) or from exposure to high beta securities. These variables may reflect the information that investors use when they make their investment and redemption decisions. For instance, mutual fund vendors and independent research advisors began reporting funds' historic bull market returns and bear market returns. The publication of this data suggests that investors demand this information and care about the conditional fund's return when they select a mutual fund from the long list of managers.

Formally, the bull and bear market returns in a period of length $t-s$, ending at time t are given by

$$R_i^U(s,t) = \sum_{s \leq u \leq t} R_{i,u}|_{R_u^m > 0} \tag{4}$$

$$R_i^D(s,t) = \sum_{s \leq u \leq t} R_{i,u}|_{R_u^m \leq 0} \tag{5}$$

respectively. To measure $R_i^U(s,t)$, for instance, form a partition $\{s = u_1, u_2, ..., u_n = t\}$ of the time interval $[s,t]$ and sum the returns R_i only for the periods u_j such that $R_{u_j}^m$ are positive. Notice that the estimates of (4) and (5) are affected by the frequency in which fund returns and market returns are monitored and accrued along the interval $[s,t]$. For instance, if the frequency is once every period of length $t-s$ then eq. (4) would yield the binary result $R_i^U(s,t) = R_{i,t}$ if $R_t^m > 0$ or $R_i^U(s,t) = 0$ if $R_t^m \leq 0$, which is uninformative regarding how much upside of the market return a has captured. It would instead just measure a fund's total excess return from period s to period t if the market return was positive and 0 otherwise. Monitoring too frequently may also be problematic since it may capture noise from market microstructure and nonsynchronous trading. Another concern is the frequency in which representative investors monitor mutual fund returns when they make their investment and redemption decisions. Next section discusses the frequencies and horizons used in the empirical tests.

3.3 Relative Down-Market Alphas, Betas, and Return

I define expressions derived from the estimates presented in sections 3.1 and 3.2 to measure a fund's downmarket relative risk-adjusted performance, as well as a proxy for fund's market timing. These quantities are the main objects used in the empirical tests of this paper, where I test whether aggregate inflow of funds are attracted by timing and downmarket relative performance.

From equations (2) and (3) I introduce the proxy for timing, which is given by

$$\delta^{\beta}_{i,t} = (\breve{\beta}^{+}_{i,t} - \breve{\beta}^{-}_{i,t}). \tag{6}$$

From now on I may refer to δ^{β} as beta-timing. Ideally, a fund delivers high up-market beta and low down-market beta, which results in positive down-market beta. This is consistent with general monotone preferences without addressing risk attitude.

The down-market relative performance of a fund is measured by

$$\delta^{\alpha}_{i,t} = (\alpha^{-}_{i,t} - \alpha^{+}_{i,t}). \tag{7}$$

From now on I may interchangeably refer to δ^{α} as alpha-timing. Risk averse investors prefer getting paid an extra dollar in the states in which their wealth is low compared to states in which wealth is high. Assuming that the market portfolio is correlated with aggregate wealth implies that investors prefer holding assets that provide incremental payoff when market declines. Precisely for that reason I anticipate that risk averse investors will prefer funds that, all else equal, have high $\delta^{\beta}_{i,t}$.

A similar return-based expression is provided by

$$D^{R}_{i,t} = R^{D}_{i}(s,t) - R^{U}_{i}(s,t). \tag{8}$$

From now on I may refer to D^{R} as return-timing. This return-based expression contains less economic information than (7) and (6) combined. However, (8) may serve as a better proxy for the information used by less sophisticated investors that compare downside risk of different funds. If they are presented with bear and bull market returns of funds they can directly calculate (8) as a way to infer the downside risk of those funds. Risk aversion implies that for a given return investors choose funds with higher $D^{R}_{i,t}$.

4 Fund Flows and the Empirical Setup

The CRSP database does not include variables which measure flows into and out of mutual funds. However, there is a simple way to accurately estimate the net flows if the data of total net assets under management and total return are available. I estimate inflows as the percentage growth of assets that are not due to returns. This proxy is standard in the literature, used before by Sirri and Tufano (1998), and denoted by

$$f_{i,t} = \frac{TNA_{i,t} - (1 + R_{i,t})TNA_{i,t-1}}{TNA_{i,t-1}} \tag{9}$$

where $f_{i,t}$ represents the percent flow into fund i at time t, and $TNA_{i,t}$ is the total net assets of fund i at time t. Expression (9) measures the percent growth of funds due to external injection or withdrawal of capital. For very small mutual funds the flows may be extremely large and volatile, and in most cases do not seem to respond to performance. To avoid this issue I exclude from the sample funds that have less than $5 million under management in any quarter.

The performance-flow literature measures the impact of performance on net flows of mutual funds. In any period one looks at how performance affects flows within the following twelve months. In the next section I provide an extensive analysis of the term structure of flows for different levels of performance. I show that twelve months of fund flows is an appropriate window length to identify the performance/flow relationship. The quantity in (9) represents the quarterly flow sampled at quarterly frequency. This expression can be summed with the next three quarters flow to form an annualized [11] version of $f_{i,t}$. The measure is denoted by

$$f_{i,t}^{year} = \sum_{s=t+1}^{t+4} f_{i,s}. \tag{10}$$

Style-flows are defined as the aggregate flows of all the funds that belong to an investment style, weighted by the total net assets of those funds. Style-flows are used as a control to isolate the flow to a specific fund which is due to it being in "hot "style.

Formally, let $\mathfrak{F}_t = \{A_t, G_t, I_t, GI_t\}$ be the set of subsets of funds that belong to a particular style

[11] I chose to sum the terms instead of geometric compounding to avoid potential biases as the one addressed by Barber and Lyon (1997). I re-examine the empirical tests using geometric analog and the results come out very similar.

at time t[12]. Now let $\sigma_{i,t} = \{S \in \mathfrak{F}_t : i \in S\}$, the set of funds that belong to the same investment style as fund i at time t. The style-flow for the style that fund i belongs to at time t is defined as

$$\phi_{i,t} = \frac{\sum_{j\in\sigma_{i,t}} TNA_{j,t} - \sum_{j\in\sigma_{i,t}} (1+R_{j,t})TNA_{j,t-1}}{\sum_{j\in\sigma_{i,t}} TNA_{j,t-1}} = \frac{\sum_{j\in\sigma_{i,t}} f_{j,t}TNA_{j,t}}{\sum_{j\in\sigma_{i,t}} TNA_{j,t}}. \tag{11}$$

Analogous to the four-quarter fund flow in (11) I define the yearly style-flow, which is given by

$$\phi_{i,t}^{year} = \sum_{s=t+1}^{t+4} \phi_{i,s}. \tag{12}$$

4.1 Performance-Flow Setup

The performance-related measures derived from (1) - (5) are estimated using 24 month windows sampled at monthly frequency. The choice for monthly frequency was made for two reasons: first, investors may define a declining market as a sequence of prolonged negative market returns, as opposed to negative return in a single trading day. In addition, the CRSP database provides monthly returns as far back as 1969, while daily or weekly returns are only available since 2001. Second, I need enough positive and negative market return datapoints to estimate the coefficients in (1) - (5). The choice of monthly frequency requires the use of about 24 datapoints for estimation. For instance, in some periods there were as many as 6 consecutive months of rising markets. In those periods the estimation errors using windows shorter than 24 months could be quite large.

Many studies have looked at the impact of past one year performance on the flows in the next 12 months. For reasons discussed above, I chose a 24 month window to measure past performance. Fund flows, however, are measured in a 12 month window. Because of data limitations there are only annual flows available at quarterly frequency. In the next sections I examine how past 24 month performance affects the flow of funds in the next 12 months. The setup is the following: in a given quarter (month T) I examine the impact of past 24 months performance in the flow of funds in the next 12 months.

Notice that first there is a pre-estimation of past performance and future fund flows using the full sample covering the period from December 1969 until March 2007. This shortens the sample

[12] A_t is the set of funds with style AGRESSIVE GROWTH at time t , G_t is the set of funds with style GROWTH at time t, I_t is the set of funds with style INCOME at time t, and GI_t is the set of funds with style GROWTH AND INCOME at time t.

used for the empirical estimation by 36 months to allow the 24 months lookback and 12 months to look forward. However, the sample size of original data is fairly large and the degrees of freedom are still quite large after discarding those 36 months of data.

5 Patterns of Performance and Fund Flows

Past studies find that funds with high absolute returns in a given year tend to attract more investment capital in the following year than mutual funds with lower returns. This suggests that in the aggregate, mutual fund customers use past returns for their investment decisions. In this section I study the term structure and time series characteristics of aggregate fund flows by plotting figures that illustrate different aspects of performance-flow relationship. For this purpose in this section performance is either the risk adjusted or absolute returns: $\breve{\alpha}$ or R. As explained in the previous section, I use 24 months of funds' returns as a predictor of fund flows. The evidence shown here serves as a building block for the full empirical analysis of flows that I provide in the next section.

The plots in figure 1 show the evolution of the average cumulative fund flows[13] within 8 quarters following extreme measurements in $\breve{\alpha}$ and R. Each of the four graphs group funds into the top or bottom quintile based on either $\breve{\alpha}$ or R. Each graph plots the term structure of fund flows for the full sample period and three additional subplots originating from (calendar-time) subperiods within the sample. The subplots suggests that there are no significant disparities in the pattern of performance-flow in different points in time.

Figure 1 shows that the top performing funds receive significantly higher inflows than the bottom performers. This is true for the full sample, as well as for any of the three subperiods. While there is fluctuation in the level of flows, the ordering of inflows for the best funds compared to worst remains unchanged.

(Insert Figure 1)

Each graph in figure 2 plots the term structure of flows by selecting funds in a similar way as in figure 1. However the three time periods are divided according to market return rankings (terciles),

[13]For each quarter ahead I estimate the value-weighted average flow in each group for every period and then take the average across time periods.

based on market return clock not calendar time. For instance, the subplot of the top tercile R^m depicts the term structure of flows for funds in periods that begin when the market's past 2-year returns have been above the 67th percentile within the entire sample period. The patterns in these four graphs are similar to the ones observed in figure 1, that is, top funds based on $\breve{\alpha}$ and R attract more money than the worst funds. Notice that the fund flows to good and bad funds display similar patterns as the ones shown in 1 regardless of how the market has performed in the previous 24 months.

(Insert Figure 2)

The graphs in figure 3 plot the time series of cumulative 1 year fund flows for the best and worst performing funds according to a sort on $\breve{\alpha}$ or R. As in the two previous graphs, top funds are the ones in the top quintile while worst funds are in the bottom quintile, based on the performance measure. The patterns across time are consistent with the term structure shown in the previous charts, that is, top performing funds receive more investment capital than the bottom funds. Flows for the top group are more volatile, and in a few time periods the top funds receive less inflows.

(Insert Figure 3)

6 Empirical Tests and Results

In this section I test more formally whether $\breve{\alpha}$ or R have a direct effect on fund flows. The coefficients in (6) - (8) capture the timing of fund performance relative to market returns. In particular, if agents are risk averse and the aggregate wealth is correlated with market moves, then investors should prefer funds with the higher δ^{α},δ^{β}, and D^R, all else equal. The risk-adjusted returns ($\breve{\alpha}$) or absolute excess returns (R) should also be included since I assume that agents care about past performance. In addition, risk averse agents prefer funds with a high δ^{α} for a given level of $\breve{\alpha}$.

Two sets of regressions are used to characterize fund flows. The first is based on proxies related to risk-adjusted returns, the "α -version". The second set is based on absolute excess returns, the "R-version". The empirical tests are based on Fama-Macbeth two-step method: first regress flows against the explanatory variables in the cross section for each period and then take a time series average of the cross-sectional estimates.

The α-version specification is expressed as a linear regression of fund flows on $\breve{\alpha}$, δ^{α}, δ^{β}, and other controls including style-flows (ϕ), size, and age of the fund:

$$f_{i,t}^{year} = b_{0,t} + b_{1,t}\breve{\alpha}_{i,t} + b_{2,t}\delta^{\alpha} + b_{3,t}\delta^{\beta} + b_{4,t}\phi_{i,t}^{year} + b_{5,t}\log(TNA_{i,t}) + b_{6,t}Age_{i,t} + e_{i,t}. \quad (13)$$

Large mutual funds tend to grow at a slower pace than smaller funds, but this pace is nonlinear in size, perhaps because of scaling. This is accounted in (13) by taking the *log* of TNA, which is the common approach in the literature. *Age* represents the number of quarters the fund has been in existence until time t. The Fama-Macbeth estimates are the time-series average of the cross-sectional estimates, i.e. $\widehat{b}_l = \frac{1}{T}\sum_{t=1}^{T}\widehat{b}_{l,t}$, $l = 0, \ldots, 6$.

Table 2 presents Fama-Macbeth estimates and the corresponding Newey-West standard errors[14] from the model presented in equation (13). I experimented different lags, and chose twelve. In the sample this window size minimized the t-stats and therefore it was associated with the highest chance of rejecting the main estimates, making it the most conservative choice of the number of lags instead of one based on economic structure of the data.

The estimates for $\widehat{b}_4$, $\widehat{b}_5$, and $\widehat{b}_6$ shown on table 2 are in line with results from previous studies. For instance, large and old funds tend to grow at a slower pace than smaller and newer funds. It is not surprising that style flows have a positive impact on fund flows. Even though $\breve{\alpha}$ is slightly different from the Jensen's one-factor alpha, both produce a positive contribution to fund flows. There is also a positive contribution from δ^{α} and from δ^{β}, which suggests that investors care about alpha-timing and beta-timing.

I measure the economic impact of $\breve{\alpha}$, δ^{α}, and δ^{β} using the estimates from Regression 1 in table 2. In the sample an extra standard deviation in $\breve{\alpha}$, δ^{α}, and δ^{β} translates into an increase in flows of about 18.9%, 2.9%, and 12.6% respectively.

(Insert table 2)

[14]I thank Mitchell Petersen and Noah Stoffman for sharing on their websites the procedures in SAS to calculate Newey West standard errors.

The R-version specification is expressed as a linear regression of fund flows on R, D^R, and the other controls as in (13):

$$f_{i,t}^{year} = c_{0,t} + c_{1,t}R_{i,t} + c_{2,t}D_{i,t}^R + c_{3,t}\phi_{i,t}^{year} + c_{4,t}\log(TNA_{i,t}) + c_{5,t}Age_{i,t} + e_{i,t}. \qquad (14)$$

This specification is very similar to (13) except that $\breve{\alpha}$, δ^α, and δ^β are replaced by R, D^R. Again, the Fama-Macbeth estimates are $\widehat{c}_l = \frac{1}{T}\sum_{t=1}^{T}\widehat{c}_{l,t}$, $l = 0, \ldots, 5$.

Table 3 presents the estimates of this specification. The controls in (14) have similar impact on flows as they do in (13). As expected, R and D^R also have a positive contribution to mutual fund flows. A one-standard deviation increase in R and D^R leads to an increase in flows of about 15.1% and 5.0% respectively.

(Insert Table 3)

6.1 Relation With Risk Factors

This section explores the relation between the funds' performance, δ's, and D^R with common risk factors. I use Fama-French factors, size (SMB) and value/growth (HML), and Momentum (MOM) factor to perform the analysis. I estimate the correlation between each timing and performance coefficient with the three factors, to illustrate which factors funds typically load on when they experience good performance or superior timing.

Table 4 shows the signs for the significant estimates that result from a Fama-MacBeth two step estimation of the coefficient on factors. I do not report the results for the factors that were not significant at the 10% level. The results on table 4 indicate that SMB is the only factor that is significant for all timing and performance coefficients, with a positive effect on R and $\breve{\alpha}$ and negative on δ^α, δ^β, and D^R. The estimation also suggests that MOM would increase R and $\breve{\alpha}$, and decrease δ^β. Finally, HML has a positive influence on $\breve{\alpha}$ and D^R. The results for R are consistent with the findings by Carhart (1997), who finds that exposure to the three Fama-French factors and MOM produce superior mutual fund performance. In this section I ignore market as a factor, even though it entered indirectly when I constructed $\breve{\alpha}$, δ^α, and δ^β.

These results suggest that a fund may achieve timing or superior performance by loading on common risk factors. However, if a given factor produces high performance but low timing ability then it would still be worthwhile for funds to have a positive weight on the factor since results from previous section suggest that performance has a higher influence on fund flows. This is consistent with the notion that funds that produce timing usually give up alpha.

(Insert Table 4)

7 Does Performance Persist?

Several studies suggest that superior mutual fund performance dissipates in a short timeframe, dismissing the belief that performance persists. I revisit this issue in a Markovian framework. First I assign each fund to one of three groups, according to the performance measured by either $\breve{\alpha}$, R, or Jensen's α: top funds, average funds, and bottom funds. Every quarter a bin is constructed by assigning funds to terciles sorted on past 24 months performance. In this framework I determine that performance persists if for each bin the chance of funds remaining in that state in the "next period"is higher than the chance of funds migrating to any of the other two states. To avoid using overlapping windows I define "next period"as being 8 quarters after assigning funds to terciles.

In each quarter I estimate the transition probabilities and average them across time to form a transition matrix, based on each of the terciles. I construct a transition matrix using the full sample of funds and another four matrices, each one constructed from one of the four investment styles: aggressive growth, growth, income&growth ,and income. Tables 5 and 6 display the estimates for the transition matrices together with standard errors. Dividing funds in styles may attenuate the endogeneity problem. That is, when style returns persist the underlying funds in that style will also likely persist, and therefore may overstate the persistence of funds as a whole.

Tables 5, 6, and 7 indicate that for the style-matrices only the performance of bottom funds persist regardless of the performance variable, $\breve{\alpha}$, R, and Jensen's α. For the top funds, returns persist only for the "INCOME "group. For the full sample the returns of all fund types (i.e. bottom, average, and top funds) persist. However, the persistence is more pronounced for the bottom performing funds, reinforcing the evidence that the performance of only those funds persist.

(Insert Table 5)

(Insert Table 6)

(Insert Table 7)

8 Conclusion

This study confirms that mutual fund investors use historic performance to pick funds that had low downside risk and good performance. In one approach I classify low downside risk funds as the ones with high down-market alpha and low down-market beta. In another approach mutual funds with low downside risk are the ones that have high down-market returns. In both cases I find that fund flows are decreasing on downside risk and increasing in performance. This confirms that investors chase funds with low downside risk. The evidence I provide is also consistent with Ang, Chen, and Xing (2006), who find that securities with more downside risk have higher returns.

A Value of $1 in Down-Markets

By definition of risk aversion,[15] the relative value of a dollar received in states in which wealth is low, is higher than the value of a dollar received in states in which wealth is higher. Analogously, an individual who's wealth change is positively related to the market's performance will prefer this contingent dollar in the states in which the market declines. In a framework where the pricing kernel is the one induced by the market express this relationship more formally as

$$\frac{\int_{D_t} \pi_t(\nu) dP(\nu)}{P(D_t)} > \frac{\int_{\Omega \setminus D_t} \pi_t(\nu) dP(\nu)}{P(\Omega \setminus D_t)} \tag{15}$$

where the asset return generating process is defined as a filtered probability space $(\Omega, \mathcal{A}_t, P)$ and $D_t = \{\omega \in \Omega : R_t^m(\omega) \leq 0\}$ denotes the event that market's excess return is negative at time t, R_t^m is the market's excess return, and π_t is the state price density process at time t. The relationship above can be easily shown in a binomial model and in a lognormal setting.

A.1 Binomial

Consider the one period binomial model with one risky security (stock) and one risk-free security (discount bond), with current prices S and $\frac{1}{1+r}$ respectively. In the next period the stock is worth SU in state 1 and SD in state 2, while the discount bond is worth 1 in both states. We impose the usual no arbitrage conditions by setting $U > 1 + r > D$. The arbitrage pricing gives us the equations

$$S = SU\pi(1)p + SD\pi(2)(1-p) \tag{16}$$

$$\frac{1}{1+r} = \pi(1)p + \pi(2)(1-p) \tag{17}$$

where $\pi(i)$ is the state price density for state i and p is the probability of state 1.

In this setting relation (15) holds if and only if $\pi(2) > \pi(1)$. If we solve for π_i we get

$$\pi(1) = \left[\frac{(1+r) - D}{1+r}\right] \frac{1}{p} \frac{1}{U - D} \tag{18}$$

[15] Here the crucial assumption is a positive risk premium for the risky asset. One way to obtain this is to assume that agents have increasing preferences and display risk-aversion. Therefore agents will hold a risky asset if and only if it has a positive risk premium.

and

$$\pi(2) = \left[\frac{U-(1+r)}{1+r}\right]\frac{1}{1-p}\frac{1}{U-D} \tag{19}$$

As is well known, risk averse agents invest a positive amount of wealth in a risky portfolio if and only if its expected return is higher than the return on a risk-free security. So assume agents are risk averse and in equilibrium they invest a positive amount of their wealth in the stock to obtain

$$[U-(1+r)]\,p - [(1+r)-D]\,(1-p) > 0. \tag{20}$$

From this relation and by inspection of (18) and (19) we obtain $\pi(2) > \pi(1)$, as we wanted.

A.2 Lognormal

Consider the continuous model with a risky security (stock) and a risk-free security (discount bond) with dynamics given respectively by

$$\frac{dS_t}{S_t} = \mu dt + \sigma dB_t \tag{21}$$

and

$$\frac{d\beta_t}{\beta_t} = rdt \tag{22}$$

where B_t is a standard Brownian motion process under the distribution P. Under no arbitrage and technical regularities the risk neutral dynamics of S_t is given by

$$\frac{dS_t}{S_t} = rdt + \sigma dB_t^\eta \tag{23}$$

where B_t^η is a standard Brownian motion process under the risk neutral distribution Q.

The excess return of the stock from time 0 to time T is positive if and only if $S_T > e^{rT}S_0$. That means that $D_T = \left[S_T \leq e^{rt}S_0\right]$. Hence,

$$S_T > e^{rT}S_0 \Leftrightarrow \left(r - \frac{\sigma^2}{2}\right)T + \sigma\sqrt{T}Z^\eta > rT \Leftrightarrow Z > \frac{\sigma}{2}T \tag{24}$$

where Z^η is a standard Gaussian random variable that represents B_T^η, i.e. $B_T^\eta = \sigma\sqrt{T}Z^\eta$.

To simplify matters we can assume, without loss of generality, $T = 1$. So we have

$$\int_{D_1} \pi_1 dP = \int_{D_1} e^{-r} f_{Z^\eta}(z) dz = e^{-r} N\left(\frac{\sigma}{2}\right) \tag{25}$$

where $N(\cdot)$ is the cdf of the standard Gaussian distribution. Analogously,

$$\int_{\Omega \setminus D_1} \pi_1 dP = \int_{\Omega \setminus D_1} e^{-r} f_{Z^\eta}(z) dz = e^{-r} N\left(-\frac{\sigma}{2}\right). \tag{26}$$

Likewise,

$$P(D_1) = \int_{D_1} f_Z(z) dz = N\left(\frac{\sigma}{2} - \frac{\mu - r}{\sigma}\right) \tag{27}$$

and

$$P(\Omega \setminus D_1) = \int_{\Omega \setminus D_1} f_Z(z) dz = N\left(\frac{\mu - r}{\sigma} - \frac{\sigma}{2}\right). \tag{28}$$

If we assume, again, that agents are risk averse it implies a positive Sharpe ratio, $\frac{\mu - r}{\sigma} > 0$. So we have

$$\frac{N\left(\frac{\sigma}{2}\right)}{N\left(\frac{\sigma}{2} - \frac{\mu - r}{\sigma}\right)} > 1 \tag{29}$$

and

$$\frac{N\left(-\frac{\sigma}{2}\right)}{N\left(\frac{\mu - r}{\sigma} - \frac{\sigma}{2}\right)} < 1, \tag{30}$$

which gives us

$$\frac{e^{-r} N\left(\frac{\sigma}{2}\right)}{N\left(\frac{\sigma}{2} - \frac{\mu - r}{\sigma}\right)} > \frac{e^{-r} N\left(-\frac{\sigma}{2}\right)}{N\left(\frac{\mu - r}{\sigma} - \frac{\sigma}{2}\right)}. \square \tag{31}$$

Example: If we set $\mu = 12\%$, $r = 7\%$, and $\sigma = 15\%$ we obtain

$$\frac{\int_{D_t} \pi_t(\nu) dP(\nu)}{P(D_t)} = \frac{e^{-r} N\left(\frac{\sigma}{2}\right)}{N\left(\frac{\sigma}{2} - \frac{\mu - r}{\sigma}\right)} = 1.4499$$

and

$$\frac{\int_{U_t} \pi_t(\nu) dP(\nu)}{P(U_t)} = \frac{e^{-r} N\left(-\frac{\sigma}{2}\right)}{N\left(\frac{\mu - r}{\sigma} - \frac{\sigma}{2}\right)} = 0.6855.$$

B Derivation of Conditional Regressions

Let $U_t = \{\omega \in \Omega : R_t^m(\omega) > 0\}$ denote the event that market's excess return is positive at time t. Likewise let $D_t = \{\omega \in \Omega : R_t^m(\omega) \leq 0\}$. For simplicity we denote $p = P(U_t)$. Now consider the conditional regressions

$$R_{i,t} \mid_{U_t} = \alpha_i^+ + \beta_i^+ R_t^m \mid_{U_t} + \varepsilon_{it}^+, \tag{32}$$

$$R_{i,t} \mid_{D_t} = \alpha_i^- + \beta_i^- R_t^m \mid_{D_t} + \varepsilon_{it}^-, \tag{33}$$

and the unconditional regression

$$R_{i,t} = \breve{\alpha}_i + \breve{\beta}_i^+ r_t^+ + \breve{\beta}_i^- r_t^- + \varepsilon_{it}, \tag{34}$$

where $R_{i,t} \mid.$ is the mutual fund's excess return, conditional on the sign of the market's excess return, $R_t^m \mid.$ is the market's excess return, conditional on the sign of the market's excess return, $r_t^+ = \max[0, R_t^m]$, and $r_t^- = \min[0, R_t^m]$. We have

$$\alpha_i^+ = E[R_{it} - \beta_i^+ R_t^m \mid U_t], \tag{35}$$

$$\alpha_i^- = E[R_{it} - \beta_i^- R_t^m \mid D_t], \tag{36}$$

and

$$\begin{aligned} \breve{\alpha}_i &= E[R_{it} - \breve{\beta}_i^+ r_t^+ - \breve{\beta}_i^- r_t^-] \\ &= E[R_{it} - \breve{\beta}_i^+ R_t^m \mid U_t]p + E[R_{it} - \breve{\beta}_i^- R_t^m \mid D_t](1-p). \end{aligned} \tag{37}$$

Since $Cov(r_t^+, r_t^-) = -E[r_t^+]E[r_t^-] > 0$ and since we do not have in general $Cov(R_t^m, R_{it} \mid U_t) = Cov(R_{i,t}, r_t^+)$, $Cov(R_t^m, R_{it} \mid D_t) = Cov(R_{i,t}, r_{i,t}^-)$, $Var(R_t^m \mid U_t) = Var(r_t^+)$, and $Var(R_t^m \mid D_t) = Var(r_t^+)$ then we do not have in general $\beta_i^+ = \breve{\beta}_i^+$ or $\beta_i^- = \breve{\beta}_i^-$. At the end of this appendix we present the value for the full expressions for the betas. If they are sufficiently close we have $\breve{\alpha}_i \approx p\alpha_i^+ + (1-p)\alpha_i^-$. In this sense $\breve{\alpha}_i$ should be close to the expected value of the up and down market alphas.

We have the following expressions

$$\beta_i^+ = \frac{Cov(R_{it}, R_t^m \mid U_t)}{Var(R_t^m \mid U_t)}, \tag{38}$$

$$\beta_i^- = \frac{Cov(R_{it}, R_t^m \mid D_t)}{Var(R_t^m \mid D_t)}, \tag{39}$$

$$b\breve{e}ta_i^+ = \frac{Var(r_t^-)Cov(R_{it}, r_t^+) + E[r_t^+]E[r_t^-]Cov(R_{it}, r_t^-)}{Var(r_t^+)Var(r_t^-) - E[r_t^+]^2E[r_t^-]^2}, \tag{40}$$

and

$$b\breve{e}ta_i^- = \frac{Var(r_t^+)Cov(R_{it}, r_t^-) + E[r_t^+]E[r_t^-]Cov(R_{it}, r_t^+)}{Var(r_t^+)Var(r_t^-) - E[r_t^+]^2E[r_t^-]^2}. \tag{41}$$

C Filtering Equity Mutual Funds

I use fund names to eliminate mutual funds that do not belong to our desired characteristics which includes style, sector, passively managed, and other features. Table 8 shows words and expressions used in the data cleaning procedure. Those words suggest the category, sector, type of management, and other characteristics. Therefore I delete funds that contain at least one of those words and expressions. However, other unused words and expressions could also suggest some undesirable features. To make sure the cleaning procedure was good enough I selected five ”random” samples consisting of 100 funds and stopped adding words/expressions to the list in table 8 until I had at most an average of 1% of undesirable funds in the selected samples.

(Insert Table 8)

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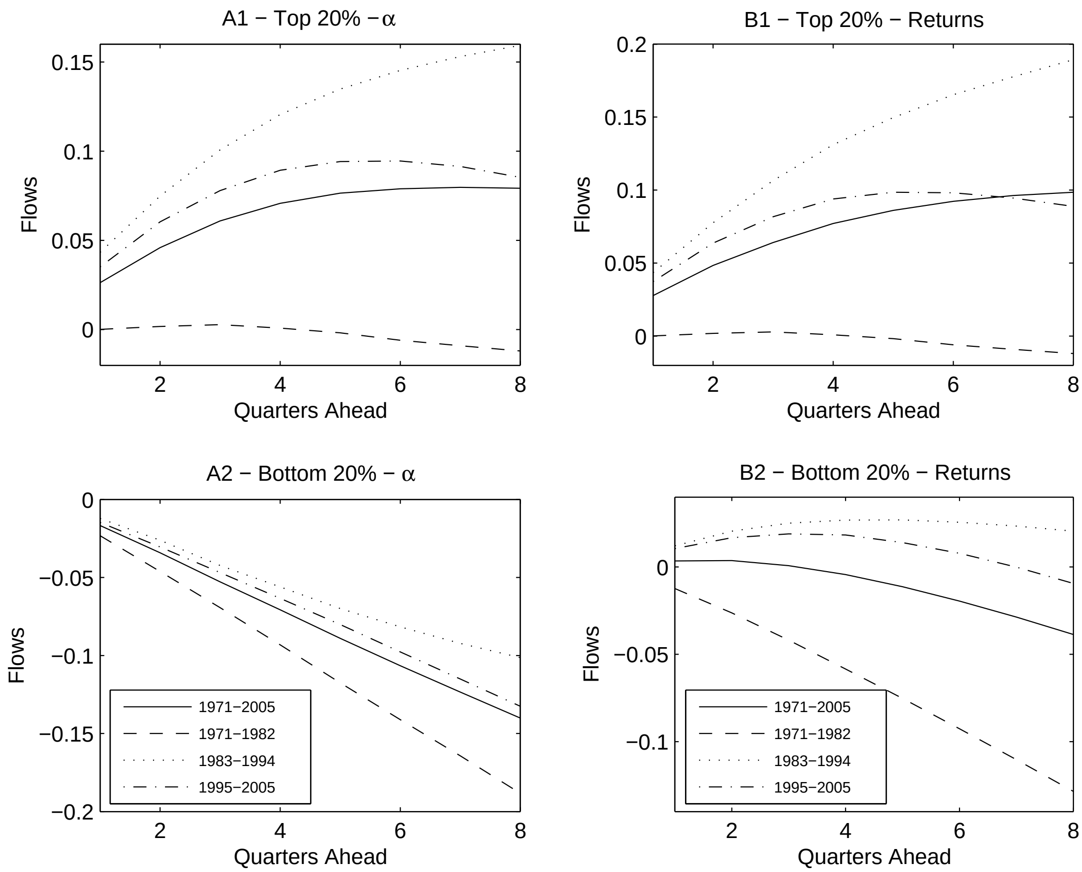

Figure 1: Term Structure of Fund Flows - Full Sample and Calendar Subsamples.

Each subplot depicts four curves that represent the weighted-average term structure of fund flows - each curve is associated with one of four time periods: full sample period (1971-2005), early period (1971-1982), middle period (1983-1994), and late period (1995-2005). In the subplots on the left funds are sorted according to $\breve{\alpha}$ while on the right funds are sorted based on R. For graph A1, fix a quarter and select the funds that belong to the top quintile of a sort on $\breve{\alpha}$. Then estimate the term structure of flows as the value-weighted average flows (measured as the percent growth of assets under management) within the next 8 quarters. The procedure is repeated for every quarter and averaged out. The final average is shown on A1. Graphs A2, B1, and B2 are constructed in a similar fashion except that funds belong to bottom $\breve{\alpha}$ -quintile, top R-quintile, and bottom R-quintile respectively.

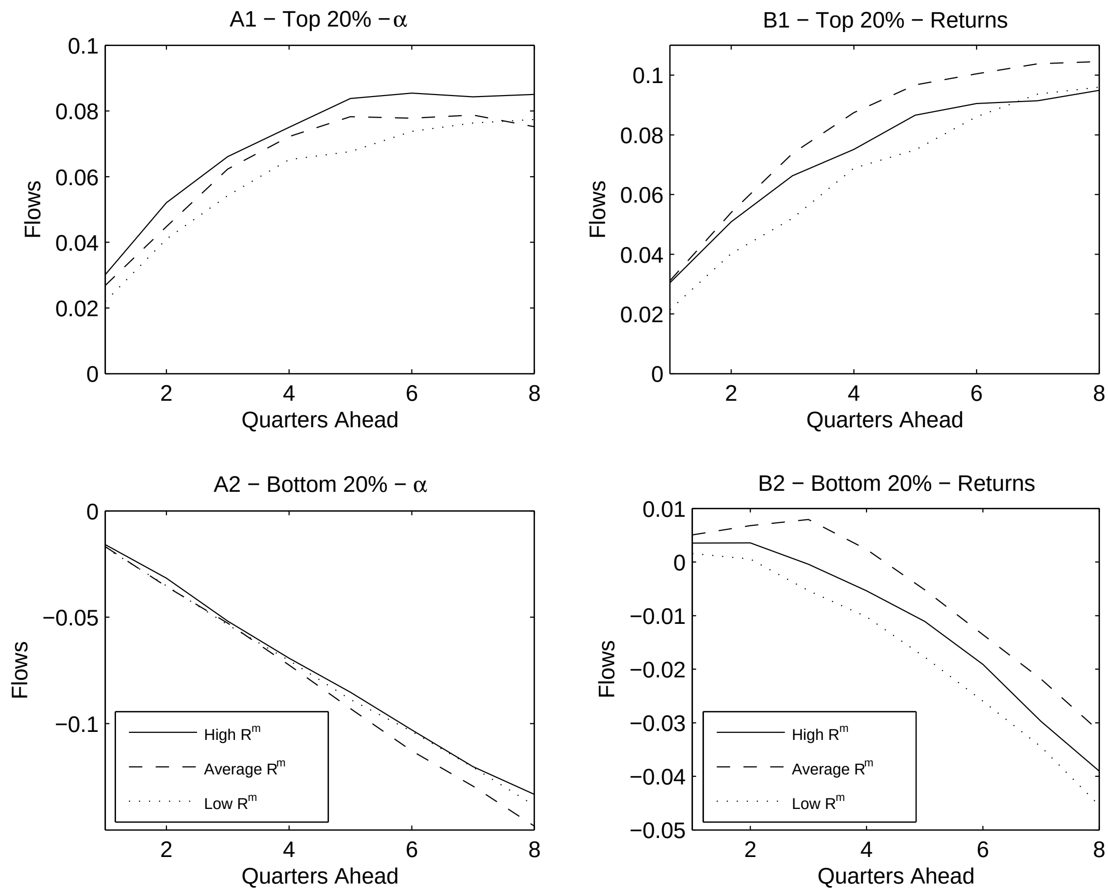

Figure 2: Term Structure of Fund Flows - by Market Return Magnitudes.

Each subplot depicts three curves that represent the weighted-average term structure of fund flows - each curve is associated with three disjoint time periods based on the magnitude of market return relative to historic returns in the full sample. For instance plot labeled ""High R^m "covers all quarters in which past 24 months market returns are in the top tercile out of all periods of consecutive 24 months sampled between 1971-2005. "Average R^m "and "Low R^m "cover funds in the middle tercile and bottom tercile, respectively. In the subplots on the left funds are sorted according to $\breve{\alpha}$ while on the right funds are sorted based on R. For graph A1, fix a quarter out of one of the R^m-terciles and select the funds that belong to the top quintile of a sort on $\breve{\alpha}$. Then estimate the term structure of flows as the value-weighted average flows (measured as the percent growth of assets under management) within the next 8 quarters. Finally the procedure is repeated for every quarter and averaged out. The final average is shown on A1. Graphs A2, B1, and B2 are constructed in a similar fashion except that funds belong to bottom $\breve{\alpha}$-quintile, top R-quintile, and bottom R-quintile respectively.

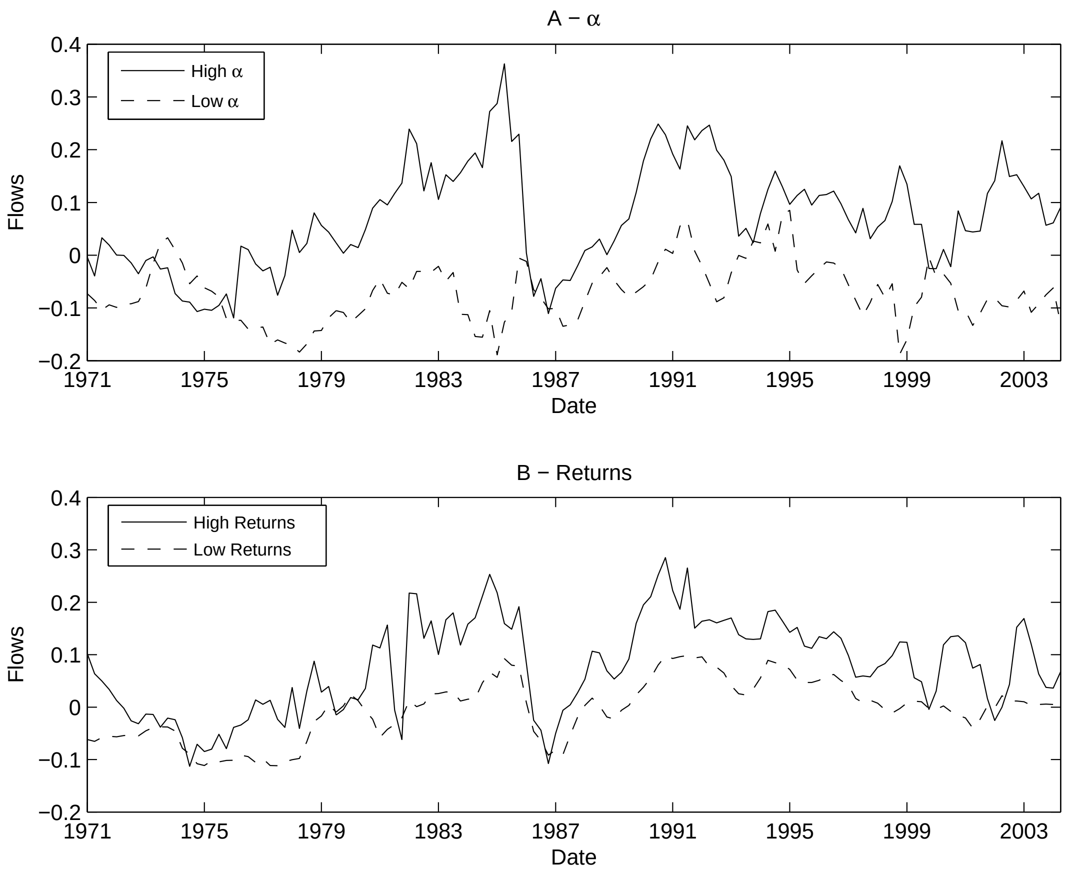

Figure 3: 12 Months Fund Flows Across Time.

In the top chart the solid line plots the value-weighted average fund flows (measured as the percent growth of assets under management) in the next 12 months for funds that are in the top quintile according to past 24 months $\breve{\alpha}$. The dashed line is the analogous version for funds in the bottom quintile sorted on $\breve{\alpha}$. The bottom chart is almost identical, except that funds are sorted based on R.

Table 1: Summary Statistics.

The table provides summary statistics for the mutual funds used in this paper. The sample includes actively managed open ended equity mutual funds with at least $15 million.

			Size of Funds($M)		Age (Years)	
	Funds	Total Assets ($B)	Mean	Median	Mean	Median
Dec-69	200	48	242	77	8.0	10.3
Dec-06	3156	3,279	1,039	177	12.9	9.5
Dec-74	188	30	161	58	10.8	13.3
Mar-02	3389	2,713	801	134	10.0	6.8

Table 2: Fama-Macbeth estimates of flows on $\breve{\alpha}$, δ^{α}, δ^{β}

The table presents the estimates and standard errors for a regressions of fund flows on $\breve{\alpha}$ (alpha), δ^{α}(alpha-timing), δ^{β}(beta-timing), and the controls ϕ(style flows), $log(TNA)$(log size of fund), and Age (in years). The estimates shown in the chart are the time series average of cross-sectional least squares regressions. The standard errors were computed using Newey-West procedure with 12 lags. Standard errors are in brackets and *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Regr 1	Regr 2	Regr 3	Regr 4	Regr 5
$\breve{\alpha}$	13.6627***	13.5299***	14.0312***	13.8423***	5.6865***
	[1.6634]	[1.6319]	[1.6999]	[1.6724]	[0.8527]
δ^{α}	1.2051**	1.3153**	1.2059**	1.3415**	
	[0.5147]	[0.5243]	[0.5258]	[0.5317]	
δ^{β}	0.2078***	0.2035***	0.2102***	0.2042***	
	[0.0221]	[0.0207]	[0.0227]	[0.0217]	
ϕ	0.5904***		0.5903***		0.7300***
	[0.0485]		[0.0574]		[0.0703]
$log(TNA)$	-0.0086***	-0.0094***	-0.0180***	-0.0190***	-0.0057**
	[0.0024]	[0.0026]	[0.0026]	[0.0027]	[0.0024]
$QuarterAge$	-0.0015***	-0.0016***			-0.0016***
	[0.0002]	[0.0002]			[0.0002]
$Constant$	0.1405***	0.1464***	0.1117***	0.1131***	0.1233***
	[0.0193]	[0.0236]	[0.0241]	[0.0298]	[0.0178]
$Mean$ $Adj-^{2}$	15.06%	13.83%	12.72%	11.16%	10.16%

Table 3: Fama-Macbeth estimates of flows on Returns.

The table presents the estimates and standard errors for Fama-Macbeth regressions of fund flows on R(Returns above the risk free), D^R(return-timing), and the controls ϕ(style flows), $log(TNA)$(log size of fund), and Age (in years). The estimates shown in the chart are the time series average of cross-sectional least squares regressions. The standard errors were computed using Newey-West procedure with 12 lags. Standard errors are in brackets and *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Regr 1	Regr 2	Regr 3	Regr 4	Regr 5
R	0.4628***	0.4568***	0.4726***	0.4673***	0.3869***
	[0.0636]	[0.0615]	[0.0652]	[0.0629]	[0.0477]
D^R	0.0860***	0.0788***	0.0949***	0.0861***	
	[0.0199]	[0.0235]	[0.0178]	[0.0210]	
ϕ	0.5304***		0.5604***		0.6649***
	[0.0678]		[0.0755]		[0.1142]
$log(TNA)$	-0.0084***	-0.0090***	-0.0181***	-0.0192***	-0.0080***
	[0.0024]	[0.0025]	[0.0027]	[0.0027]	[0.0025]
$QuarterAge$	-0.0016***	-0.0017***			-0.00157***
	[0.0002]	[0.0003]			[0.0002]
$Constant$	0.0895***	0.0895***	0.0628***	0.0586**	0.0609***
	[0.0197]	[0.0188]	[0.0240]	[0.0241]	[0.0177]
$Mean$ $Adj-^2$	14.37%	13.49%	11.80%	10.56%	12.63%

Table 4: Influence of Common Risk Factors on Timing and Performance.

The table presents the sign and level of significance of the Fama French common factors (plus Momentum) that significantly explain funds' timing and performance coefficients used in this study. the performance coefficients are δ^{α}(alpha-timing), δ^{β}(beta-timing), $\breve{\alpha}$(alpha), D^R(return-timing), and R(Returns above the risk free). The factors are value/growth (HML), size (SMB), and momentum (MOM). For each coefficient a Fama-MacBeth two-step regression of factors on the mutual fund coefficient identifies the factors that significantly explain the funds' coefficient.

	HML	SMB	MOM
δ^{α}		-*	
δ^{β}		-*	-***
$\breve{\alpha}$	+*	+**	+***
D^R	+***	-***	
R		+*	+***

Table 5: Persistence of $\breve{\alpha}$.

The tables present estimated transition matrices of performance of a fund based on $\breve{\alpha}$. In each period funds are sorted and assigned into bins based on the terciles of performance ($\breve{\alpha}$). After 8 quarters the distribution of funds assigned to new bins determine the estimated transition probabilities. These probabilities are averaged out across time and the standard errors are computed, and represented in brackets. In the top table the procedure is performed for all funds in my sample, while in the other tables funds are grouped based on the style that they belong.

(I - A) FULL SAMPLE

		S(t+1)		
		Top 1/3	Mid 1/3	Lower 1/3
S(t)	Top 1/3	36.8%	29.3%	34.0%
		[1.1%]	[0.6%]	[1.0%]
	Mid 1/3	25.8%	39.5%	34.8%
		[0.6%]	[0.5%]	[0.6%]
	Lower 1/3	29.6%	30.2%	40.3%
		[1.1%]	[0.6%]	[1.1%]

(I - B) AGGRESSIVE GROWTH

		S(t+1)		
		Top 1/3	Mid 1/3	Lower 1/3
S(t)	Top 1/3	34.7%	30.5%	34.8%
		[1.1%]	[0.7%]	[1.1%]
	Mid 1/3	26.4%	34.3%	39.3%
		[0.9%]	[0.7%]	[0.9%]
	Lower 1/3	23.9%	30.2%	45.9%
		[0.9%]	[0.7%]	[1.0%]

(II - B) INCOME

		S(t+1)		
		Top 1/3	Mid 1/3	Lower 1/3
S(t)	Top 1/3	35.3%	29.3%	35.4%
		[1.6%]	[1.1%]	[1.6%]
	Mid 1/3	24.6%	36.9%	38.5%
		[1.1%]	[1.0%]	[1.3%]
	Lower 1/3	32.1%	31.1%	36.8%
		[1.8%]	[1.1%]	[1.9%]

(III - B) INCOME GROWTH

		S(t+1)		
		Top 1/3	Mid 1/3	Lower 1/3
S(t)	Top 1/3	35.0%	30.7%	34.3%
		[1.1%]	[0.7%]	[1.1%]
	Mid 1/3	26.5%	35.6%	37.8%
		[0.7%]	[0.6%]	[0.8%]
	Lower 1/3	27.9%	29.3%	42.8%
		[1.0%]	[0.6%]	[1.0%]

(IV - B) GROWTH

		S(t+1)		
		Top 1/3	Mid 1/3	Lower 1/3
S(t)	Top 1/3	34.7%	30.5%	34.7%
		[1.0%]	[0.7%]	[1.0%]
	Mid 1/3	29.3%	35.2%	35.5%
		[0.6%]	[0.7%]	[0.7%]
	Lower 1/3	27.4%	31.1%	41.6%
		[0.9%]	[0.7%]	[1.0%]

Table 6: Persistence of Returns

The tables present estimated transition matrices of performance of a fund based on R. In each period funds are sorted and assigned into bins based on the terciles of performance (R). After 8 quarters the distribution of funds assigned to new bins determine the estimated transition probabilities. These probabilities are averaged out across time and the standard errors are computed, and represented in brackets. In the top table the procedure is performed for all funds in my sample, while in the other tables funds are grouped based on the style that they belong.

(I - A) FULL SAMPLE

		S(t+1)		
		Top 1/3	Mid 1/3	Lower 1/3
S(t)	Top 1/3	37.6%	30.0%	32.4%
		[1.2%]	[0.5%]	[1.3%]
	Mid 1/3	29.8%	37.0%	33.1%
		[0.7%]	[0.6%]	[0.7%]
	Lower 1/3	28.3%	29.7%	42.0%
		[1.3%]	[0.8%]	[1.5%]

(I - B) AGGRESSIVE GROWTH

		S(t+1)		
		Top 1/3	Mid 1/3	Lower 1/3
S(t)	Top 1/3	32.9%	31.8%	35.3%
		[1.2%]	[0.8%]	[1.3%]
	Mid 1/3	29.5%	34.6%	35.8%
		[0.9%]	[0.8%]	[0.8%]
	Lower 1/3	28.2%	28.4%	43.5%
		[1.2%]	[0.8%]	[1.4%]

(II - B) INCOME

		S(t+1)		
		Top 1/3	Mid 1/3	Lower 1/3
S(t)	Top 1/3	40.4%	28.1%	31.5%
		[1.9%]	[1.2%]	[1.8%]
	Mid 1/3	26.2%	40.1%	33.7%
		[1.4%]	[1.3%]	[1.5%]
	Lower 1/3	28.5%	29.4%	42.0%
		[1.9%]	[1.4%]	[2.0%]

(III - B) INCOME GROWTH

		S(t+1)		
		Top 1/3	Mid 1/3	Lower 1/3
S(t)	Top 1/3	37.2%	29.8%	33.1%
		[1.1%]	[0.6%]	[1.2%]
	Mid 1/3	27.1%	38.5%	34.4%
		[0.7%]	[0.6%]	[0.7%]
	Lower 1/3	29.6%	28.1%	42.3%
		[1.2%]	[0.7%]	[1.2%]

(IV - B) GROWTH

		S(t+1)		
		Top 1/3	Mid 1/3	Lower 1/3
S(t)	Top 1/3	35.6%	29.1%	35.3%
		[1.2%]	[0.7%]	[1.3%]
	Mid 1/3	31.4%	34.3%	34.3%
		[0.7%]	[0.6%]	[0.9%]
	Lower 1/3	27.9%	30.8%	41.3%
		[1.2%]	[0.8%]	[1.3%]

Table 7: Persistence of Jensen's α.

The tables present estimated transition matrices of performance of a fund based on Jensen's α. In each period funds are sorted and assigned into bins based on the terciles of performance (α). After 8 quarters the distribution of funds assigned to new bins determine the estimated transition probabilities. These probabilities are averaged out across time and the standard errors are computed, and represented in brackets. In the top table the procedure is performed for all funds in my sample, while in the other tables funds are grouped based on the style that they belong.

(I - A) FULL SAMPLE

		S(t+1)		
		Top 1/3	Mid 1/3	Lower 1/3
S(t)	Top 1/3	35.8%	30.3%	33.8%
		[1.1%]	[0.5%]	[1.2%]
	Mid 1/3	27.8%	38.8%	33.5%
		[0.7%]	[0.5%]	[0.7%]
	Lower 1/3	28.0%	28.9%	43.1%
		[1.1%]	[0.6%]	[1.3%]

(I - B) AGGRESSIVE GROWTH

		S(t+1)		
		Top 1/3	Mid 1/3	Lower 1/3
S(t)	Top 1/3	32.7%	32.1%	35.2%
		[1.2%]	[0.8%]	[1.4%]
	Mid 1/3	26.8%	35.2%	38.0%
		[0.8%]	[0.8%]	[0.9%]
	Lower 1/3	25.2%	27.5%	47.3%
		[1.1%]	[0.7%]	[1.3%]

(II - B) INCOME

		S(t+1)		
		Top 1/3	Mid 1/3	Lower 1/3
S(t)	Top 1/3	34.9%	32.7%	32.4%
		[1.6%]	[1.1%]	[1.7%]
	Mid 1/3	30.3%	35.8%	33.9%
		[1.2%]	[1.0%]	[1.3%]
	Lower 1/3	31.0%	28.4%	40.6%
		[1.5%]	[1.2%]	[1.7%]

(III - B) INCOME GROWTH

		S(t+1)		
		Top 1/3	Mid 1/3	Lower 1/3
S(t)	Top 1/3	36.1%	29.4%	34.5%
		[1.2%]	[0.6%]	[1.2%]
	Mid 1/3	24.2%	38.3%	37.5%
		[0.6%]	[0.6%]	[0.7%]
	Lower 1/3	27.1%	29.7%	43.2%
		[1.1%]	[0.7%]	[1.2%]

(IV - B) GROWTH

		S(t+1)		
		Top 1/3	Mid 1/3	Lower 1/3
S(t)	Top 1/3	35.1%	29.9%	35.0%
		[1.0%]	[0.7%]	[1.1%]
	Mid 1/3	29.4%	35.3%	35.2%
		[0.6%]	[0.6%]	[0.7%]
	Lower 1/3	27.1%	29.9%	43.0%
		[0.9%]	[0.7%]	[1.1%]

Table 8: Data Cleaning - Filtering Equity Mutual Funds

Procedure to eliminate index, non-equity, international, real estate, sector, and precious metal funds. The left column shows the fund type in consideration and the right column shows the word and expression that implies that the fund with that word or expression in its name is one of the type in consideration, and must, therefore, be deleted from the database.

Type of funds	Delete fund if name contains one of the following word/expression
Money Market, Bonds,	Bd, Bond, Bonds, Cash, Convertible, Debt, Duration, Exempt, Real Estate, and Life, Federal, Fixed Inc, Floating, Free, Fxd Inc, Government, Govt, Cycle, Gov't, Grade, Gvt, Insured, Investment Grade, M/M, Maturity, MNY, Money, MTG, Backed, Adj Rate, Adjustable Rate, Federal Mtge, Mortgage, Mtg Backed, Muni, Municipal, Municipals, Obligations, Real Estate, REIT, T/E, T/F, Treasury, TSY, Tx,TXFR, Yield, 2004, 2007, 2010, 2013, 2016, 2019, 2020, 2022,2030, 2040, 2050
International	Asia, Developing markets, Emerg, Emerging, Eurofund, Europe, European, Foreign, Germany, Global, Global, International, Internatl, INTL, INT'L, Japan, World, Worldwide
Index	Index
Precious Metals	Metal, Metals, Precious