The 52-Week High, Momentum, and Predicting Mutual Fund Returns

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Abstract

The 52-week high share price has been shown by George and Hwang (2004) to carry significant predictive ability for individual stock returns, dominating other common momentum-based trading strategies. This study examines the performance of trading strategies for mutual funds based on (1) an analogous 1-year high measure for the net asset value of fund shares, (2) prior extreme returns, and (3) fund sensitivity to stock return momentum. All three measures have significant, independent, predictive ability for fund returns. Further, each produces a distinctive pattern in momentum profits, whether measured in raw or risk-adjusted returns, with profits from momentum loading being the least transitory. Nearness to the 1-year high and recent extreme returns are significant predictors of fund monthly cash flows, whereas fund momentum loading is not.

Evidence of momentum in stock returns is abundant in the literature. The phenomenon of stock price momentum at the one year horizon is extensively documented by Jegadeesh and Titman (1993). Carhart (1997) shows that momentum is an important common factor in explaining the cross-section of stock returns. The Carhart 4-factor pricing model, consisting of the Fama-French 3-factor model augmented with a factor for momentum, has since become a staple in asset pricing and performance studies. The robustness of the momentum phenomenon has been noted by Fama (1998) and re-confirmed by Jegadeesh and Titman (2001). Rouwenhorst (1998) finds significant momentum profits in twelve other countries, showing that momentum is an internationally robust phenomenon. Moskowitz and Grinblatt (1999) find that momentum is related to industry, Hoitash and Krishnan (2008) link momentum to speculative herding by investors in high-tech stocks, and Chordia and Shivakumar (2002) show that price momentum payoffs are related to macroeconomic variables.

More recently, George and Hwang (2004) show that the 52-week high stock price carries significant predictive ability for individual stock returns. Trading strategies based on the 52-week high are found to dominate strategies based on either prior mean returns or prior industry returns. This finding is surprising in that it is such a simple and readily available measure, and is not based on explicit performance. They posit that this result is driven by investor psychology in the form of an anchoring bias that is based on the recent maximum price.

While stock price momentum is a robust phenomenon, there is considerable debate as to whether it may be translated into profitable trading after transaction costs. Jegadeesh and Titman (2001) and Korajczyk and Sadka (2004) find that momentum profits appear to be positive even after taking into account trading costs. However, Grundy and Martin (2001) and Lesmond, Schill, and Zhou (2004) argue that momentum trading does not appear profitable after transaction costs. In particular, Grundy and Martin note that short-term momentum investing in stocks is a volatile strategy that frequently delivers negative payoffs.

The question of whether momentum investing strategies are more efficacious at the mutual fund level has received surprisingly less attention. There are several reasons to expect that momentum may be exploitable at the fund level. In particular, there is substantial reduction in volatility in moving to a diversified environment, seasonals such as the January effect are mitigated at the fund level, and transaction costs for many funds are minimal.

In considering mutual fund performance, we may distinguish between three distinct issues: (1) Can a fund manager consistently beat the market through security selection (alpha-seeking) or timing (beta-shifting)? (2) Can a fund investor beat the market by picking a skilled manager and sticking with that fund? (3) Can a fund investor beat the market by picking some transitory fund characteristic(s) and re-balancing periodically? I note that the third hypothesis does not require the presence of fund manager skill.[1] In this study, I take an agnostic position on the question of whether fund managers are able to add value through skilled active management. Instead, I address the third hypothesis outlined above. Namely, I examine whether a fund investor can outperform a neutral benchmark by tracking some transitory fund characteristic and re-balancing periodically. But what characteristic best predicts mutual fund performance?

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[1] A considerable body of literature examines the performance of mutual funds and the question of whether some fund managers have superior investment skills. Jensen (1968), Gruber (1996), and Carhart (1997), among others, show that mutual funds on average underperform their relevant benchmarks after expenses. However, a number of studies have documented the tendency of performance to persist among some funds (Grinblatt and Titman (1989, 1992), Grinblatt, Titman, and Wermers (1995), Hendricks, Patel, and Zeckhauser (1993), Goetzmann and Ibbotson (1994), Brown and Goetzmann (1995), and Gruber (1996)). Carhart (1997) and Sapp and Tiwari (2004) demonstrate that stock return momentum can account for the persistence in performance and apparent profitability of persistence-based investment strategies. Wermers (2004) finds that fund return persistence is partially driven by cash flows from investors who chase performance, and Avramov and Wermers (2006) relate performance persistence to industry-based fund manager skill. Kacperczyk, Sialm, and Zheng (2005) find that industry concentrated funds perform better than funds that are diversified across industries, attributing this difference to better stock picking and style timing abilities of the concentrated funds.

Studies by Hendricks, Patel, and Zeckhauser (1993) and Carhart (1997), among others, have demonstrated that mutual fund returns are predictable based on past fund returns. Sapp and Tiwari (2006) show that mutual fund risk-adjusted returns are predictable based on fund sensitivity to stock return momentum. The information content of nearness to the 52-week high price for individual stocks documented by George and Hwang (2004) may also have an analogous effect for the shares of mutual funds, a possibility which has not been examined elsewhere in the literature. However, the explanation suggested by George and Hwang for the predictive power of the 52-week high for stock returns would not be applicable to mutual funds. This is because, unlike the price of a share of stock, the net asset value (NAV) of a mutual fund is not materially affected by investor supply and demand for shares of the fund.[2] Still, it is possible that the fund share price level may to some extent reflect the tendency of the underlying stocks to be affected by recent highs.

In this paper I examine and compare the profitability of three momentum-based trading strategies for mutual funds. Specifically, funds are ranked each month using either (1) the prior 6-month fund return, (2) the estimated fund momentum factor loading, or (3) nearness to the 1-year high NAV. Fund raw returns and risk-adjusted returns are then examined over holding periods extending from one to twelve months.

Profits to the strategies based on each ranking criterion are first examined individually. I find that the fund 1-year high NAV has significant predictive power for both raw returns and risk-adjusted returns, with profits nearly rivaling those from a strategy based on recent large returns. Profits to long-short strategies are substantial, though only hypothetical when applied to mutual funds. I therefore focus primarily on long strategies. A strategy which buys and then

[2] There may be a small second-order effect due to price impact if the fund's stock trades are sufficiently large.

holds the top 10% of funds for six months earns a significant annual risk-adjusted excess return of 4.92%, 2.88%, and 3.60%, when funds are ranked according to prior 6-month return, momentum factor loading, and 1-year high NAV, respectively. When examining the top 30% of funds, the corresponding annual risk-adjusted excess returns are 2.88%, 1.56%, and 2.40% for the three respective strategies.

I also examine the three momentum strategies within a regression setting, where the marginal contribution of each may be measured. Following the approach of George and Hwang (GH 2004), I track the individual performance of each momentum strategy by regressing fund returns on a series of fund rank dummy variables representing either a long or short position in each of the three trading strategies. The resulting coefficients show the return to each strategy after the effects from the other strategies have been hedged out. I find that each momentum measure contains significant, independent information about future fund performance, whether performance is measured in raw returns or risk-adjusted returns.

Most interesting, however, is the pattern observed in the behavior of the profitability of each measure over time. Profits based on extreme recent returns are generally the largest, and along with those based on the nearness to the one-year high, disappear at the 12-month post-formation horizon. Although, as also noted by Carhart (1997), fund momentum loading is a poor predictor of raw returns, I find that it is an excellent predictor of *risk-adjusted profits* over time. These profits die out more slowly than those from the other two trading strategies and do not disappear after 12 months. Indeed, these risk-adjusted excess returns are significantly positive out to a 24-month post-ranking horizon. This is interesting in that the "one-year" momentum effect is seen to extend to two post-ranking years for mutual funds when momentum is measured by a 4-factor model momentum loading. Overall, these results are robust to ranking funds based on either prior gross or net returns, and are robust to whether alphas are computed from portfolios or fund-by-fund. Finally, I confirm that these results are robust to the exclusion of load funds from the sample, which highlights the fact that momentum is an investable strategy at the fund level with minimal cost.

The presence of three distinct significant predictors of mutual fund performance suggests that momentum profits may be decomposed into multiple sources. The longer-term predictive ability of fund momentum loading may be indicative of a more persistent source of momentum sensitivity in the fund's holdings —for example, if the fund holds stocks with higher individual momentum sensitivities, either due to manager style or to chance. The component of fund returns that is due to exposure to the Fama-French factors has been "hedged out" in the process of estimating fund momentum loading. Furthermore, the correlation between momentum loading and either of the other two momentum measures is approximately zero. Accordingly, momentum loading is perhaps better able to identify a more persistent aspect of fund momentum. More temporary momentum effects may be reflected in the occurrence of recent extreme returns and in the nearness of the NAV to its 1-year high.

How may we synthesize the results of this study with papers which find evidence of a smart money effect? In particular, Gruber (1996) and Zheng (1999) report that investors have selection ability, in that the short-term performance of funds that experience net cash inflow appears to be significantly better than the short-term performance of funds that experience net cash outflow. For example, Zheng (1999) reports an annual three-factor alpha of 0.89% for positive fund cash flows and -0.32% for negative cash flows. Sapp and Tiwari (2004) show that this effect is related to stock return momentum. Keswani and Stolin (2008) argue that, after controlling for stock return momentum, there is still a smart money effect. All of these studies agree that the smart money effect is transitory. One possible explanation for the smart money effect is that sophisticated investors have the ability to identify superior fund managers and invest accordingly. This is argued by Gruber (1996) and Keswani and Stolin (2008). However, the transitory nature of the effect militates against this interpretation. Realizing this, Keswani and Stolin (2008) argue that price pressure from fund inflows, growing fund size, and imitation of the fund's strategy may cause superior performance to dissipate. An alternative explanation, which is favored here, is that investors are simply chasing transitory fund characteristics, such as recent returns, nearness to the year high price, or fund momentum loading. The fact that they do this crudely and unsystematically leads to the relatively weak smart money effect documented in the literature.

Finally, in order to gauge which fund characteristics investors seem to chase, I examine the determinants of mutual fund flows at the monthly frequency. Past studies have almost unanimously relied on either annual or quarterly fund flows for such an analysis. With the availability of monthly TNA data in the CRSP mutual fund database since 1991, I argue that it is now preferable to exploit the larger number of observations available over the more recent sample period rather than relying on fewer, less frequent observations. Using monthly imputed cash flows from 1991 through 2004, I find that both prior returns and nearness to the year high NAV are significant predictors of fund cash flows, whereas fund momentum loading is not. The evidence suggests that investors chase the two indicators of short-term momentum which lead to more transitory profits. However, fund momentum loading, which investors do not seem to track, appears to be the best indicator of relatively stable, longer-term momentum profits.

I. Data and Method

A. Mutual Fund Sample

This study examines equity funds in the CRSP Mutual Fund database spanning the period 1970-2004. The sample includes all domestic common stock funds that exist at any time during the period 1970 to 2004. I exclude international funds, sector funds, specialized funds, and balanced funds, because these funds may have risk characteristics that are not spanned by the factors driving the returns of most other mutual funds. I also remove redundant share classes from the sample, retaining only one share class per fund. For each fund, an attempt was made to identify and retain a dominant share class by examining length of fund history and total net assets. This final sample contains 4,514 fund-entities comprising 30,640 fund-years and descriptive statistics are reported in Panel A of Table I. Over the first 22 years of the sample period the number of funds is fairly stable, going from 299 in 1970 to 376 in 1991. In 1992 the number of funds jumps to 817, and climbs steadily to 2,862 by 2004. As a robustness check, and to emphasize the implementability of momentum-based trading strategies from an investor's perspective, I also examine a narrowed sample which removes load funds. This smaller sample contains 2,845 fund-entities comprising 15,830 fund-years and descriptive statistics are reported in Panel B of Table I.

B. Measuring the One-Year High NAV

Fund net asset values (NAVs) are reported to the public at the end of each trading day, meaning each fund has approximately 252 NAVs per year. However, except very recently, the CRSP mutual fund database only reports month-end NAVs. As a result, when computing the maximum NAV over 12 monthly observations, the value obtained will be downward biased compared to the true daily maximum NAV. I next describe how to correct for this bias using an adjustment that is based on a result derived for pricing lookback options in Broadie, Glasserman, and Kou (BGK 1999).

Adopting the standard assumption that equity price evolves according to a geometric Brownian motion process, price is assumed to be continuously observed. If instead we observe price at a discrete number of intervals *m*, then using a result found in equation (8) of BGK, the maximum computed over *m* price observations may be adjusted using either a first-order or second-order approximation. The first-order adjustment depends on volatility, but not the drift, and consists of multiplying the observed maximum price $\mathrm{NAV}_{\max}$ by a correction factor:

$$\mathrm{NAV}_{\max} \exp\left(\frac{\beta_1 \sigma \sqrt{T}}{\sqrt{m}}\right) \tag{1}$$

where T is the horizon in years, σ is the volatility of returns, and $\beta_1 = -\varsigma(1/2)/\sqrt{2\pi} \approx 0.5826$, with ζ being the Riemann zeta function. If a more exact approximation is desired, then a correction factor including a second-order term may be constructed. Specifically, define

$$\gamma = \frac{1}{2}\left[\frac{\sigma}{\sqrt{2\pi}} \exp\left(-\frac{\mu^2 T}{2\sigma^2}\right) - \left(\mu\sqrt{T}\,\Phi\left(\mu\sqrt{T}/\sigma\right) - \frac{\mu\sqrt{T}}{2}\right)\right] \tag{2}$$

where $\mu = r - (1/2)\sigma^2$ and Φ denotes the cumulative standard normal distribution. Then the second-order correction is given by

$$\mathrm{NAV}_{\max} \exp\left(\frac{\beta_1 \sigma \sqrt{T}}{\sqrt{m}} + \frac{\gamma\sqrt{T} + (1/2)\beta_2 \sigma^2 T}{m}\right) \tag{3}$$

where $\beta_2 \approx 0.425$.

Finally, I note that in practice fund NAVs are not observed more frequently than 252 times per year. For purposes of this study, where option pricing is not in view, the actual observable frequency of the fund NAV is the relevant standard against which to assess bias.

Therefore, I adjust the measured maximum for the bias in going from 252 to 12 annual observations. This is equivalent to dividing the adjustment factor computed for m = 12 by the adjustment factor computed for m = 252. For example, letting T = 1 for the current application, the first order adjustment becomes

$$\mathrm{NAV}_{\max} \exp\left(\beta_1 \sigma \left(\frac{1}{\sqrt{12}} - \frac{1}{\sqrt{252}}\right)\right) \tag{4}$$

The above describes the theoretical basis for adjusting the observed maximum NAV for infrequent sampling. In practice, there are three approaches that I can take: (1) note the problem and use the biased estimates anyway, (2) impose a universal correction factor to every fund, or (3) estimate a correction factor for each fund separately based on its sample mean and standard deviation. Use of the biased maximum estimates will on average make share prices appear “closer” to the current price, leading to less dispersion, and potentially less information, in the nearness measure. However, implementing a bias correction for each individual fund faces the following difficulty. Due to heteroskedasticity, periods of brief but volatile returns in the fund’s history can result in a high sample standard deviation and a relatively large bias correction which is applied to all time periods. The effect is to over-correct for bias and introduce noise into the sampling procedure. Schemes to sample volatility over short windows face additional measurement difficulties. Therefore, I choose a middle approach and impose a moderate universal bias correction factor on each fund. For the approximate average time series mean and standard deviation in the mutual fund sample, r = 0.10 and σ = 0.20, the first-order approximation yields a correction factor of 1.0266 and the second-order correction factor is 1.0298.[3] Accordingly, I correct for the downward bias of the measured maximum due to

[3] Comparison of the maximums obtained from daily and monthly sampled S&P500 index values as well as from numerous funds selected at random also reveals a typical bias of about 3%.

relatively infrequent sampling of NAV by applying an adjustment factor of 1.03 for each fund in month t in the following manner. First, I obtain the maximum NAV over months t – 1 through t – 11 and multiply by the correction factor 1.03. The 1-year high is then the greater of this number or the NAV in month t:

$$high_{i,t} = \max\left(1.03 \times \max\left(NAV_{i,t-11}, \ldots, NAV_{i,t-1}\right), NAV_{i,t}\right) \tag{5}$$

I note that whether I use the maximum NAV unadjusted for bias, implement the universal correction as described, or apply an estimated bias correction on an individual fund basis, the results are very similar and none of the conclusions of the paper is affected. However, the simple universal correction, given its resulting smoothed forecasting power, appears to strike a good balance in capturing the probable maximum for most funds without over-correcting the estimate. Finally, in a manner analogous to George and Hwang (2004), I compute the nearness of the current NAV to the 1-year high as

$$\frac{NAV_{i,t}}{high_{i,t}} \tag{6}$$

C. Momentum Trading Strategies

I analyze three momentum investing strategies for mutual funds in this paper. Specifically, funds are ranked on either (1) the prior six-month fund return, (2) the estimated fund momentum factor loading, or (3) nearness to the one-year high NAV. In each case, investors form a portfolio based on fund rankings according to the momentum measure and hold the portfolio for a horizon of anywhere from 1 to 12 months. I report results for 3, 6, and 12-month holding periods as well as month-by-month returns. Although studies examining stock return momentum such as George and Hwang (2004) control for the January effect, I find this is unnecessary when examining mutual fund momentum as fund returns in January are not significantly different from returns in other months.

The first investment strategy I adopt is based on prior returns and applies to mutual funds the approach taken by Jegadeesh and Titman (JT 1993) for individual stocks. They define strategies based on a ranking period and a holding period, where, for example, a (6, 6) strategy means the securities are ranked over a period of six months and then held for a period of six months. Like JT, Grundy and Martin (2001), and George and Hwang (2004), I adopt a six-month ranking period based on past returns. I follow the approach of Grundy and Martin (2001) in ranking funds based on the past six-month cumulative return, $\sum_{\tau=t-6}^{t-1} r_{i\tau}$, and I use reported returns, which are net of expenses. This is the most relevant measure to investors, and likely what investors would also rank funds based upon. However, since mutual fund expense ratios comprise a predictable component of investor net returns, as a robustness check I also run all tests after adding back expenses to remove any effect. I find this makes little difference as the results are practically identical whether I rank funds under the JT strategy using either net returns or gross returns.

For each fund I measure the cumulative return over the past six months, rank funds into deciles based on this prior return, and then form two portfolios. Securities ranked in the top 10% constitute the winner portfolio and those in the bottom 10% constitute the loser portfolio. Each of these portfolios is equally-weighted. I also examine portfolios formed from the top 30% and bottom 30% of funds. The strategy examined by JT for stocks is to hold for a given horizon a self-financing portfolio that is long the winner and short the loser portfolios. Examining long-short strategies is revealing of the full information content of a given momentum measure.

However, in this paper I primarily focus on returns to the long portfolio since short-selling is not possible for most mutual fund shares.

The method employed by JT for computing strategy returns over a holding period of, say, six months is the following. In any particular month t, the return to winners is calculated as the equally weighted average of the month t returns from six separate winner portfolios, each formed in one of the six consecutive prior months t – 6 to t – 1. Hence, the investment portfolio is rebalanced each month, with one-sixth of the holdings being replaced. Consecutive formation periods thus overlap by five months. The same is done to compute the month t return to the loser portfolio. The result is that returns to the strategy are observed monthly, beginning in the seventh month of the sample period. Returns to alternative holding periods such as 3 and 12 months are measured in similar fashion.

The second trading strategy I analyze is based on the fund's sensitivity to stock return momentum. In order to quantify this, each month for fund i the four-factor model of Carhart (1997) is estimated using the prior 24 months of returns:[4]

$$r_{i,t} = \alpha_i + \beta_{1,i} RMRF_t + \beta_{2,i} SMB_t + \beta_{3,i} HML_t + \beta_{4,i} UMD_t + e_{it}\,. \tag{7}$$

Here, $r_{i,t}$ is the monthly return on fund i in excess of the one-month T-bill return; RMRF is the excess return on a value-weighted market portfolio; and SMB, HML, and UMD are returns on zero-investment factor-mimicking portfolios for size, book-to-market, and one-year momentum in stock returns. The regression coefficient β_4 measures the sensitivity of the fund's holdings to underlying stock return momentum while holding market, size, and value exposure constant. An investment strategy based on the estimated momentum factor loading is then implemented in

[4] I also test momentum loadings estimated over a long (36-month) window and a short (12-month) window, and results in each case are very similar. The choice of a 24-month estimation window reflects a reasonable tradeoff between estimation precision and capturing the fund's most recent momentum sensitivity.

similar fashion to the JT strategy, with funds being ranked each month based on $\hat{\beta}_4$ instead of the prior six-month return.

The third trading strategy I examine is based on ranking funds each month t according to $\frac{NAV_{i,t}}{high_{i,t}}$, the fund's (bias-corrected) nearness to its 1-year high NAV. This measure is analogous to the 52-week high measure implemented by George and Hwang (2004). Note that since the NAV for month t is included when measuring the 12-month high, this nearness measure is bounded above by one.

Finally, in analyzing fund performance, I report raw returns and returns that have been adjusted for market risk and style using the Fama-French 3-factor benchmark. This is equivalent to the model in equation (7), minus the fourth factor for stock return momentum. Note that I do not include a momentum factor in the performance benchmark as it is precisely momentum profits which I am seeking to isolate and quantify, rather than explain. Due to the need for preliminary data to estimate various performance measures for each fund, the investment strategies are all implemented beginning in January of 1973.

II. Results

A. Profits to Momentum Strategies

I first analyze the returns to each momentum strategy individually. Panel A of Table II reports raw return results based on the top 10% and bottom 10% of funds for each of the three trading strategies. Several results immediately stand out. Average returns to a winner minus loser long-short portfolio from the JT strategy based on prior six-month fund performance are the largest at each holding period reported and, over a 12-month holding period, average 0.48% per month. Fund momentum loading is seen to lack significant predictive ability for fund raw returns at all holding periods reported, although it turns out to be an informative predictor of risk-adjusted returns as I will discuss below. Nearness to the 1-year high NAV is a significant predictor of returns for holding periods up to one year, with average returns from a winner minus loser strategy of 0.26% per month over 12 months.

Panel B of Table II reports fund returns that have been adjusted for market risk and style factors using the Fama-French 3-factor model. These estimates are derived by regressing the time series of monthly average returns generated by each strategy on the contemporaneous Fama-French factors.[5] Results show that all three of the ranking criteria produce large significant alphas to a long-short strategy for the extreme decile portfolios over either 3, 6, or 12 months. For example, the average monthly return per dollar long for a 6-month holding period is 0.63%, 0.36%, and 0.48% for a strategy based on prior return, fund momentum loading, and nearness to the 1-year high, respectively. Focusing only on long strategies, each of the ranking criteria again produces significant risk-adjusted excess returns at each holding period reported. For example, the average monthly return for a 6-month holding period is 0.41% for the winner portfolio based on prior return, 0.24% for the winner portfolio based on fund momentum, and 0.30% for the winner portfolio based on nearness to the 1-year high.

Table III reports results based on strategies which hold the top 30% or bottom 30% of funds ranked by each respective strategy. The purpose of examining a broader definition of winners and losers is to see how deep into the ranked cross-section of funds each momentum effect cuts. As expected, the profitability of all three strategies is attenuated as we move away

[5] These are portfolio time series alphas. I also compute average alphas for each strategy by estimating an alpha for each fund in each month from factor realizations and fund factor loadings estimated over the prior 36 months. Results are very similar, but appear more stable through time, and with higher significance levels. These results are reported in the appendix.

from the extreme rankings. However, in terms of raw returns, strategies based on prior 6-month returns and nearness to the 1-year high are both still profitable out to a holding period of 12-months. Looking at risk-adjusted returns, the profitability of all three strategies is significant at all horizons, with the exception of momentum loading at the 12-month horizon. Focusing on a holding period of six months, the risk-adjusted average monthly return to a long position in the winner portfolio is 0.24%, 0.13%, and 0.20% for strategies based on prior returns, momentum loading, or the 1-year high, respectively. The overall change in going from extreme 10% to extreme 30% of funds is a decline in profitability of 42% for the prior return strategy, 44% for the momentum loading strategy, and a decline of 35% for the 1-year high strategy. Thus, each of the strategies declines similarly when including lower-ranked funds, with the 1-year high strategy losing effectiveness slightly less quickly in moving away from the extreme tails of the distribution.

One limitation of reporting returns over increasingly longer holding periods is that the month-by-month profitability of each strategy is not clear due to averaging over the entire holding period. Momentum-based strategies would generally be expected to decline in profitability the further we move from the ranking period. Therefore, in order to observe the post-formation behavior of each ranking criterion, I calculate the monthly post-ranking returns to each strategy over a 12-month horizon. The resulting term structure of momentum profits is summarized graphically in Figure 1.

Panel A of Figure 1 displays raw returns to a strategy that buys the top decile (winner) portfolio and sells the bottom decile (loser) portfolio as defined by each of the three ranking criterion. A strategy based on prior returns is clearly dominant in terms of raw performance over the entire 12-month horizon. For strategies based on either prior returns or nearness to the year high NAV, profits are relatively large soon after formation, decline with distance from the ranking period, and disappear within 12 months from the time of formation. The raw return profitability of a long-short strategy based on momentum loading is flat and relatively small at all horizons compared to the other two strategies, hovering just above zero. Panel B shows raw returns to a long-short strategy for the top and bottom 30% of funds. The pattern displayed by each strategy is similar to the case of extreme decile portfolios in Panel A, but the magnitude of profits is smaller.

Panel A of Figure 2 displays monthly risk-adjusted returns to a strategy which buys the top decile of funds according to each of the three ranking criterion. For each post-ranking horizon, the reported return is the alpha obtained by regressing the time series of portfolio returns on the contemporaneous Fama-French factors. Several interesting results emerge when looking at risk-adjusted returns. A strategy based on prior returns again largely dominates, but to a lesser extent. Of particular note is the relative stability of profits to a strategy based on fund momentum loading. The profitability of all three strategies converges at about the 10-month post-ranking horizon, and the momentum loading profits finish strongest over the final two months.

B. Regression Analysis of Momentum Profits

I next compare the three strategies simultaneously using Fama–MacBeth (1973) style cross-sectional regressions. Since at least two of the strategies, those based on prior return and nearness to the 1-year high, are highly correlated, I wish to isolate the contribution from each of the three strategies while controlling for the other two. The approach here mirrors George and Hwang (2004). The dependent variable in these regressions is the month t return to fund i, $R_{i,t}$. The independent variables are dummies that indicate whether fund i is held (either long or short) in month t as part of one of the three strategies. The resulting coefficients on the dummies give the return to each strategy when the effects of the other strategies have been removed, or hedged out. Specifically, the profit from a winner or loser portfolio in month *t* for a (6, 6) strategy can be calculated as the equal-weighted average of returns to six portfolios, each formed in one of the six past successive months $t - j$ (for $j = 1$ to $j = 6$). This is the method employed to produce the returns reported in Table II. However, now the marginal contributions of the various portfolios formed in month $t - j$ to the month *t* return are obtained by estimating the following regression:

$$R_{it} = b_{0jt} + b_{1jt} JH_{i,t-j} + b_{2jt} JL_{i,t-j} + b_{3jt} BH_{i,t-j} + b_{4jt} BL_{i,t-j} + b_{5jt} YH_{i,t-j} + b_{6jt} YL_{i,t-j} + e_{it} \qquad (8)$$

where $YH_{i,t-j}$ ($YL_{i,t-j}$) is the 1-year high winner (loser) dummy that takes the value of 1 if the 1-year high measure for fund *i* is ranked in the top (bottom) 10% in month $t - j$, and zero otherwise. The 1-year high measure in month $t - j$ is the ratio of net asset value (NAV) in month $t - j$ to the maximum NAV achieved in months $t - j - 12$ to $t - j$. The dummy *JH* (*JL*) indicates a winner (loser) by JT's prior return ranking criterion, and *BH* (*BL*) indicates a winner (loser) by ranking on fund momentum factor loading, for the period between months $t - j - 6$ and $t - j$. Besides looking at extreme deciles, I also analyze returns for strategies based on the top 30% and bottom 30% according to each ranking criterion. The coefficient estimates of a given independent variable are averaged over $j = 1, 2, 3$ for (6, 3) strategies, and $j = 1, . . . , 6$ for (6, 6) strategies, and $j = 1, \ldots, 12$ for (6, 12). The numbers reported for the strategy return in the tables are the time-series averages of these averages. To obtain risk-adjusted returns, I further run time series regressions of these averages (one regression for each average series) on the contemporaneous Fama–French factor realizations to hedge out the factor exposure. The numbers reported for risk-adjusted returns are intercepts from these time-series regressions.

Panel A of Table IV reports results for the extreme top and bottom 10% of funds for each momentum strategy. In terms of raw returns, any strategy, long, short, or self-financing, based on prior returns is consistently significantly profitable over holding periods of 3, 6, and 12 months. Profits based on fund momentum loading are not significant at any horizon for the winner, loser, or long-short strategy. A strategy which buys the 1-year high winner shows profits which are consistently positive and significant over all three holding periods. The magnitude of profits to a long strategy is largest for the JT portfolio, which offers roughly double the raw return of a long strategy based on the 1-year high.

When looking at risk-adjusted returns, an interesting reversal in the pattern of profits occurs. It is first of all important to note that all three momentum strategies show independent predictive power for risk-adjusted returns. Although alphas from the JT strategy again dominate, profits to a long strategy based on momentum factor loading are now seen to be consistently positive and significant at all three holding periods. These profits also tend to dominate those from either a long strategy or long-short strategy based on the 1-year high. Focusing on a holding period of six months, the risk-adjusted average monthly return to a long position in the winner portfolio is 0.27%, 0.19%, and 0.15% for strategies based on prior returns, momentum loading, or the 1-year high, respectively.

Panel B of Table IV reports results based on strategies which hold the top 30% or bottom 30% of funds ranked by each respective strategy. We again see that the profitability of all three strategies is attenuated as we move away from the extreme rankings. However, in terms of raw returns, long strategies to both JT and 1-year high are still profitable. In terms of risk-adjusted returns, all three momentum strategies are still significantly profitable at all three holding periods. Focusing on a holding period of six months, the risk-adjusted average monthly return to a long position in the winner portfolio is 0.18%, 0.12%, and 0.07% for strategies based on prior returns, momentum loading, or the 1-year high, respectively. The overall change in going from extreme 10% to extreme 30% of funds is a decline in profitability of about one-third for the prior return and momentum loading strategies, but a decline of over one-half for the 1-year high strategy. Thus, the 1-year high strategy effectiveness is increasingly subsumed by the other two measures of momentum in moving away from the extreme tails of the distribution.

As discussed earlier, one limitation of reporting average returns over increasing holding periods is that the month-by-month post-ranking behavior of each strategy is not clear. In order to observe the post-formation behavior of each ranking criterion, I calculate the monthly post-ranking hedged returns to each strategy over a 12-month horizon. The results of this exercise are summarized graphically in Figure 3, where several interesting results emerge. First, the magnitude of profitability of the three strategies converges at about the 9-month horizon. Second, a strategy based on momentum loading appears the least profitable of the three initially, but quickly overtakes the 1-year high strategy and is also the most stable through time. Last, while the profitability of the JT prior return strategy and the 1-year high strategy decline and dissipate by month 11, the profitability of momentum loading remains positive and significant. The next section will examine the long-term behavior of each strategy in more detail.

C. Long-Term Persistence of Momentum Profits

I now extend the post-ranking horizon to 24 months and focus on the profitability of each strategy over the post-ranking period extending from 13 to 24 months after portfolio formation. The results are presented graphically in Figure 4. Panel A shows the alphas for the top 10% winners from each individual strategy. Each estimate of post-ranking monthly return has an associated regression *t*–statistic and most of these are individually significant for each strategy over the first 12 months after ranking, but not during the second 12 months. However, given the pattern of steadily declining but positive alphas observed over time, a joint test of the returns over the second 12-month period is more informative than the individual alpha *t*–statistics. Referring to Panel A, the mean alpha over months 13–24 for a strategy that is long the top 10% portfolio ranked on momentum loading is 0.13% (*t*–stat = 5.37).[6] The corresponding numbers for a strategy based on prior returns and the one-year high are 0.06% (*t*–stat = 2.30) and 0.03% (*t*–stat = 1.39), respectively.

The multiple-regression, or hedged, alphas in Panel B of Figure 4 present a similar pattern to those in the stand-alone case, with profits from a strategy based on momentum loading showing the most persistence over a two-year post-ranking horizon. The mean alpha over months 13–24 for a strategy that is long the top 10% portfolio ranked on momentum loading is 0.13% (*t*–stat = 6.17). The corresponding numbers for a strategy based on prior returns and the one-year high are 0.02% (*t*–stat = 0.99) and 0.01% (*t*–stat = 0.68), respectively. Focusing only on the last six post-ranking months, 19–24, the mean alpha for the momentum loading strategy is still significant at 0.09% (*t*–stat = 3.19).

The profitability of a trading strategy based on fund momentum loading is both economically and statistically significant out to two full years after ranking, on average exceeding that of strategies based on either recent extreme returns or nearness to the 1-year high NAV. This suggests that fund momentum loading is linked to a less transitory aspect of momentum than either of the latter two measures. Perhaps fund momentum loading, which is estimated over a 24-month window, is picking up a characteristic of the fund's stock holdings which makes them more prone to momentum cycles. One may speculate that the stocks which give a fund a relatively large momentum loading are more likely to be affected by industry

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[6] The joint test-statistic for the mean return of each strategy over *N* months is computed as $\frac{\sqrt{N}}{N}\sum_{i=1}^{N} t - stat_i$, where *N* = 12 and $t\text{–}stat_i$ are the 12 consecutive alpha regression *t*-statistics beginning in month 13. Since the regressions generating the *t*-statistics each have between 360 and 372 observations, the joint statistic is approximately normally

momentum or individual investor biases, and these features are less transitory than the aspect of momentum being captured by recent returns or nearness to the high NAV.

Over the long term it has been shown, for example by Carhart (1997), that funds seem unable to maintain a high momentum loading. This suggests that the effect described here is not a result of managers consistently following a momentum strategy in individual securities. However, the practical aspect of this finding is that longer-term momentum investors (those who do not wish to rebalance more frequently than once every 1-2 years) would be well served by investing in a fund with a high current momentum loading.

D. Momentum Profits for No-load Funds

Each of the three momentum strategies I have analyzed is profitable among the full sample of mutual funds. But in order to be implementable on an ongoing basis, re-balancing at a frequency of 6-24 months would be required, and the presence of load fees would make this impracticable. Therefore, in order to investigate the profitability of an ongoing momentum investment strategy which is implementable in practice, I now focus on the sub-set of no-load funds. Results based on a stand-alone analysis of each strategy for the top 10% of funds are presented in Table V and results for the top 30% of funds are presented in Table VI.

The individual strategy results for the no-load sample are very similar to those of the full sample. If anything, they would have to be characterized as stronger. Statistical significance levels are all comparable and the magnitudes of the strategy profits are generally the same or larger. Results from a regression analysis of all three strategies are reported in Table VII. Here we see that the statistical significance of the estimated regression coefficients is generally lower, particularly in the case of the fund momentum loading strategy, though the magnitudes of the

distributed.

marginal contributions of each strategy are similar to those found for the full sample of funds. Given the stronger individual strategy results for no-load funds reported in Tables V and VI, this is likely due to the reduction in the number of observations stemming from the exclusion of load funds from the sample. In particular, the number of no-load funds during many years in the first half of the sample period is less than 100, leaving fewer than 10 funds in a given decile rank. Overall, the no-load fund results confirm the profitability of the three trading strategies examined for the subset of funds having minimal transaction costs, thus highlighting that fund-based momentum trading appears to be implementable in practice.

E. Sub-Period Analysis

As noted earlier, the number of mutual funds in the sample increases dramatically in 1992. In order to examine whether the profitability of momentum based trading strategies differs based on the number of funds, I divide the sample period into two sub-samples: 1973-1991 and 1992-2004. In un-tabulated results, I find that the patterns seen in the full sample are reflected in the two separate sub-samples. Specifically, the momentum trading strategy based on the past six-month return dominates in both periods, with profits from the past returns strategy and the one-year high strategy declining at about the 9-month horizon. However, the *t*-statistics are generally weaker due to the decreased number of observations in each sub-sample. In terms of hedged momentum trading profits, all three strategies show independent statistically significant profits in both time periods, with the exception of the one-year high strategy. This strategy does not yield statistically significant profits in the early period. Also, momentum profits appear stronger in the later period, while being somewhat muted in the earlier period. The larger number of funds in the later period likely gives rise to greater dispersion in fund holdings and styles, and hence in momentum effects.

F. Determinants of Fund Cash Flows

Prior studies examining the determinants of fund cash flows have almost exclusively relied on either annual or quarterly imputed net cash flows.[7] While early studies used annual flow data, with the advent of the CRSP mutual fund database in the late 1990's, quarterly cash flows could be readily computed from quarterly TNA data for a large number of funds. Although this data is only available at the quarterly frequency in the CRSP database prior to 1991, monthly TNA figures have been provided by CRSP for the more recent time period. As the number of months for which this data is available has expanded with the passage of time, there are now more data points available in working strictly with monthly cash flows over the shorter sample period 1991-2004 than in using quarterly data over the entire sample period. The monthly frequency is also more desirable so as not to average out over a quarter potential shorter-term investor responses to momentum effects. The importance of this last consideration has been argued by Keswani and Stolin (2008). Hence, I focus on monthly cash flows over this shorter sample period for the analysis that follows.

I regress fund net cash flows on the three measures of momentum described in this paper, while controlling for a number of fund characteristics. Since large funds have larger dollar cash flow, I normalize cash flow by the beginning month TNA. Explanatory variables include the logarithm of lagged fund TNA, lagged percentage cash flow, turnover, expenses, and total load fees. The regressions are performed cross-sectionally each month in Fama-MacBeth style, and the time series of resulting coefficients are averaged. Results are reported in Table VIII.

Similar to the finding of many other studies, such as Chevalier and Ellison (1997) and Sirri and Tufano (1998), recent returns are seen to be a strong predictor of fund cash flows.

Nearness to the high NAV is also a significant predictor of investor cash flows. However, momentum loading is not significant in any of the regressions. This finding is consistent with that of Sapp and Tiwari (2004), who examine quarterly net cash flows and are also unable to detect any significant explanatory power from momentum loading. When controlling for previous fund cash flow and fund size, recent returns and nearness to the 1-year high remain significant. While fund turnover and load fees lack explanatory power for monthly fund cash flow, expenses are negatively correlated with fund flows. Overall, the evidence suggests that investors chase the two indicators of short-term momentum which lead to relatively more transitory profits. Investor cash flows do not track fund momentum loading, though it appears to be the best indicator of relatively stable, longer-term momentum profits.

III. Conclusion

The 52-week high share price has been shown by George and Hwang (2004) to carry significant predictive ability for individual stock returns, dominating other common momentum-based trading strategies. This paper examines and compares the performance of three momentum trading strategies for mutual funds, including an analogous one-year high measure for the net asset value of mutual fund shares. Strategies based on prior extreme returns and on fund exposure to stock return momentum are also examined. Results show that all three measures have significant, independent, predictive ability for fund returns. Further, each measure produces a distinctive pattern in momentum profits over a one-year investment horizon, whether profits are measured in raw returns or risk-adjusted returns. Profits based on extreme recent returns are generally the largest, and along with those based on the nearness to the one-year high, disappear

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[7] For example, studies which employ annual cash flows include Gruber (1996), Chevalier and Ellison (1997), Sirri and Tufano (1998), and Jain and Wu (2000). Studies which examine quarterly cash flows include Zheng (1999) and

at the 12-month post-formation horizon. An active momentum trading strategy where rebalancing every 3-6 months were feasible would likely produce the most benefit if based on recent extreme returns. When market, size, and distress factors are "zeroed out," estimated momentum loading shows an impressive ability to forecast longer-term returns. Risk-adjusted profits based on momentum loading are found to be the most stable and do not disappear up to a 24-month post-formation horizon.

The finding that all three measures have significant, independent predictive power for fund returns suggests that there are multiple aspects of fund momentum which are being captured. Profits based on recent extreme returns and nearness to the one-year high are more volatile and fleeting, while those based on stock return momentum loading are more stable and persistent. George and Hwang (2004) suggest that the predictive ability of the 1-year high may be due to an adjustment and anchoring bias on the part of individual investors. They reason that investors are reluctant to bid a stock's price above the recent high, even if the information warrants it, and are similarly reluctant to sell when the price is far below the recent high. However, this argument does not apply to the share price of mutual funds, as fund NAVs are strictly determined by the underlying stock prices. The only plausible explanation would seem to be that this is a residual effect from the underlying 52-week high phenomenon at the individual stock level, though it is rather surprising that this effect is not washed out within a diversified portfolio.

The literature shows that investors appear to exhibit fund selection ability and this smart money effect is related to stock return momentum. Since all studies documenting a smart money effect agree that the effect is transitory, it seems unlikely that investors are identifying skilled

Sapp and Tiwari (2004). An exception is Keswani and Stolin (2008), who use monthly cash flows.

managers, but rather they are crudely chasing performance. A more systematic approach to active mutual fund investing would periodically rebalance according to one of the measures identified in this study, with the trailing six-month return relative to that of all other funds serving as the most effective signal. The profits from all three strategies analyzed here are substantial compared to those actually earned by new money flowing into mutual funds.

Appendix

As a robustness check, I compute risk-adjusted returns to each univariate momentum strategy using an alternative, fund-by-fund method. Specifically, alphas are estimated as one-month abnormal returns for each fund in each month from factor realizations and fund factor loadings estimated over the prior 36 months:

$$\alpha_{i,t} \equiv r_{i,t} - r_f - \hat{\beta}_{1,i,t-1} RMRF_t - \hat{\beta}_{2,i,t-1} SMB_t - \hat{\beta}_{3,i,t-1} HML_t \tag{A1}$$

Results are presented for the full sample in Table A1. Panel A reports average alphas for the top and bottom 10% of funds, and Panel B gives results for the top and bottom 30%. Three main results emerge when comparing the fund-by-fund alphas to the portfolio time series alphas. First, the *t*-statistics for the fund-by-fund alphas are generally larger. Second, the magnitude of the fund-by-fund returns is generally smaller. This is especially true for the prior return and 1-year high strategies. Also, the disparity between the two alpha measures is more pronounced for shorter holding periods, which leads to the third and last observation: the fund-by-fund alphas are more stable than the portfolio alphas over the three reported holding periods. The two alpha measures are compared graphically in Figure A1, which shows the term structure of one-month alphas over 24 post-ranking months for a long-short strategy in the extreme decile portfolios. The raw returns to each long-short strategy are also shown for comparison. Time series alphas tend to track raw returns, whereas fund-by-fund alphas are flatter. Figure A2 shows the fund-by-fund alphas for each momentum strategy in the same graph. Overall, evaluating strategy performance by either method leads to the same set of conclusions described in the paper.

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Table I
Sample Descriptive Statistics

The full sample in Panel A includes all U.S. equity mutual funds that existed at any time during January 1970 through December 2004. Redundant share classes within the same fund are excluded. Sector funds, international funds, balanced funds and specialized funds are excluded. The final sample includes 4,514 funds comprising 30,640 fund-years. The monthly net cash flow for fund *j* in month *t* is $NCF_{j,t} = TNA_{j,t} - TNA_{j,t-1}(1 + r_{j,t})$, where, $NCF_{j,t}$ denotes the monthly net cash flow for fund *j* in month *t*, $TNA_{j,t}$ is the total net assets for fund *j* at the end of month *t*, and $r_{j,t}$ is the fund's return in month *t*. Monthly cash flow as a percentage of the prior month TNA is also reported. Turnover is defined as the minimum of aggregate purchases or sales of securities during the year, divided by the average TNA. Maximum total load fees equals maximum front-end load fees plus maximum sales charges paid when withdrawing money from the fund. The expense ratio is the percentage of total investment that shareholders pay for the fund's operating expenses. Nearness to the high NAV is calculated as $NAV_{i,t}/high_{i,t}$ where $high_{i,t}$ is the bias-adjusted highest NAV of fund *i* during the 12 month period that ends the last day of month *t*. Momentum factor loading is the momentum beta coefficient estimated for each fund from the prior 24 months using a Fama-French 3-factor model that is augmented with a fourth factor for 1-year momentum. Panel B excludes load funds from the sample, resulting in 2,845 unique funds comprising 15,830 fund-years. For each item, I analyze the cross-section in each year from 1970 to 2004. The reported statistics are computed from the time-series of the 420 monthly cross-sectional means for each item. Statistics for cash flows are based on the shorter time period 1991-2004, when monthly data is available.

Panel A: All funds

	Mean	Median	25^{th} percentile	75^{th} percentile	Standard Deviation
Total Net Assets ($ millions)	628.89	476.28	375.58	824.90	420.40
Monthly Net Cash Flow ($ millions)	3.32	3.69	1.69	5.33	3.54
Monthly Net Cash Flow (%)	2.01	1.89	1.08	2.90	1.25
Expense Ratio (%/year)	1.12	1.09	0.98	1.27	0.15
Turnover (%/year)	79.65	79.16	72.42	87.75	20.30
Maximum Total Load Fee (%)	3.81	3.75	2.28	5.10	1.50
Monthly Net Return (%)	0.95	1.28	-1.91	4.11	4.66
Nearness to the One-Year High NAV	0.89	0.91	0.84	0.95	0.08
Momentum Factor Loading	0.06	0.04	0.02	0.08	0.06

Panel B: No-load funds

	Mean	Median	25^{th} percentile	75^{th} percentile	Standard Deviation
Total Net Assets ($ millions)	334.37	329.63	29.81	575.87	307.97
Monthly Net Cash Flow ($ millions)	3.58	3.54	1.72	5.81	3.78
Monthly Net Cash Flow (%)	2.40	2.20	1.22	3.46	1.55
Expense Ratio (%/year)	1.13	1.11	1.06	1.17	0.11
Turnover (%/year)	81.57	77.94	71.72	90.10	22.00
Monthly Net Return (%)	0.95	1.29	-1.91	4.22	4.73
Nearness to the One-Year High NAV	0.89	0.91	0.84	0.95	0.09
Momentum Factor Loading	0.06	0.04	0.02	0.07	0.06

Table II
Profits from Momentum Strategies: Top and Bottom 10%

The table reports average monthly returns from January 1973 to December 2004 for three different momentum investing strategies. Each month funds are ranked into deciles according to one of three criteria: (1) the prior 6-month return, (2) the fund momentum factor loading estimated from a 4-factor model over the prior 24 months, (3) the high NAV from the prior 12 months. The return to a strategy follows the method of Jegadeesh and Titman (1993) and in a given month is the average return from the portfolios formed in each of the prior months in the holding period. Panel A reports the time series mean of the cross-sectional mean returns for the top 10% and bottom 10% of funds for holding periods of 3, 6, and 12 months, respectively. Panel B reports the alpha from a time series regression of the cross-sectional mean return from the top and bottom decile portfolios on the Fama-French factors for holding periods of 3, 6, and 12 months, respectively. The sample includes all unique equity mutual funds in the CRSP mutual fund database. The full sample includes 4,514 funds comprising 30,640 fund-years. All returns are percent per month. *T*-statistics are in parenthesis.

Panel A: Fund Returns

	3-month			6-month			12-month		
Ranking criterion	Top	Bottom	Difference	Top	Bottom	Difference	Top	Bottom	Difference
Prior 6-month returns	1.42	0.76	0.66	1.45	0.84	0.61	1.38	0.90	0.48
	(5.08)	(2.84)	(3.14)	(5.19)	(3.25)	(3.31)	(4.92)	(3.73)	(3.28)
Momentum factor loading	1.15	0.99	0.16	1.19	1.03	0.16	1.19	1.06	0.14
	(3.83)	(4.22)	(0.94)	(3.99)	(4.43)	(0.97)	(4.02)	(4.61)	(0.85)
Prior 1-year high NAV	1.30	0.86	0.44	1.33	0.94	0.40	1.28	1.02	0.26
	(5.78)	(3.03)	(2.80)	(5.81)	(3.36)	(2.81)	(5.60)	(3.85)	(2.53)

Panel B: 3-factor Alphas

	3-month			6-month			12-month		
Ranking criterion	Top	Bottom	Difference	Top	Bottom	Difference	Top	Bottom	Difference
Prior 6-month returns	0.42	-0.27	0.69	0.41	-0.22	0.63	0.30	-0.19	0.49
	(3.64)	(-2.48)	(3.37)	(3.93)	(-2.29)	(3.51)	(3.50)	(-2.55)	(3.63)
Momentum factor loading	0.25	-0.15	0.39	0.24	-0.13	0.36	0.20	-0.12	0.32
	(2.63)	(-2.06)	(2.98)	(2.61)	(-1.83)	(2.87)	(2.32)	(-1.85)	(2.76)
Prior 1-year high NAV	0.31	-0.21	0.52	0.30	-0.18	0.48	0.22	-0.11	0.33
	(3.68)	(-2.30)	(3.49)	(3.92)	(-2.13)	(3.56)	(3.80)	(-1.65)	(3.40)

Table III
Profits from Momentum Strategies: Top and Bottom 30%

The table reports average monthly returns from January 1973 to December 2004 for three different momentum investing strategies. Each month funds are ranked into deciles according to one of three criteria: (1) the prior 6-month return, (2) the fund momentum factor loading estimated from a 4-factor model over the prior 24 months, (3) the high NAV from the prior 12 months. The return to a strategy follows the method of Jegadeesh and Titman (1993) and in a given month is the average return from the portfolios formed in each of the prior months in the holding period. Panel A reports the time series mean of the cross-sectional mean returns for the top 30% and bottom 30% of funds for holding periods of 3, 6, and 12 months, respectively. Panel B reports the alpha from a time series regression of the cross-sectional mean return from the top and bottom decile portfolios on the Fama-French factors for holding periods of 3, 6, and 12 months, respectively. The sample includes all unique equity mutual funds in the CRSP mutual fund database. The full sample includes 4,514 funds comprising 30,640 fund-years. All returns are percent per month. *T*-statistics are in parenthesis.

Panel A: Fund Returns

	3-month			6-month			12-month		
Ranking criterion	Top	Bottom	Difference	Top	Bottom	Difference	Top	Bottom	Difference
Prior 6-month returns	1.25	0.84	0.41	1.29	0.89	0.39	1.25	0.95	0.31
	(4.96)	(3.34)	(2.96)	(5.06)	(3.63)	(3.15)	(4.91)	(4.03)	(3.12)
Momentum factor loading	1.08	1.00	0.08	1.12	1.03	0.08	1.12	1.06	0.06
	(3.95)	(4.40)	(0.69)	(4.08)	(4.57)	(0.71)	(4.11)	(4.73)	(0.56)
Prior 1-year high NAV	1.21	0.89	0.32	1.23	0.96	0.27	1.20	1.02	0.18
	(5.30)	(3.37)	(2.74)	(5.34)	(3.66)	(2.62)	(5.20)	(4.04)	(2.49)

Panel B: 3-factor Alphas

	3-month			6-month			12-month		
Ranking criterion	Top	Bottom	Difference	Top	Bottom	Difference	Top	Bottom	Difference
Prior 6-month returns	0.24	-0.19	0.43	0.24	-0.17	0.40	0.18	-0.13	0.31
	(3.10)	(-2.41)	(3.15)	(3.33)	(-2.34)	(3.35)	(3.01)	(-2.26)	(3.44)
Momentum factor loading	0.14	-0.09	0.23	0.13	-0.08	0.22	0.10	-0.07	0.18
	(2.21)	(-1.65)	(2.60)	(2.16)	(-1.53)	(2.54)	(1.72)	(-1.44)	(2.25)
Prior 1-year high NAV	0.21	-0.16	0.37	0.20	-0.13	0.33	0.14	-0.09	0.23
	(3.24)	(-2.23)	(3.27)	(3.38)	(-1.97)	(3.27)	(3.03)	(-1.60)	(3.18)

Table IV
Comparison of Momentum Trading Strategies

Each month from January 1973 to December 2004, either 3 (j = 1, 2, 3), 6 (j = 1, …, 6), or 12 (j = 1, …, 12) cross-sectional regressions of the following form are estimated for investment holding periods of 3, 6, and 12 months, respectively:

$$R_{it} = b_{0jt} + b_{1jt} JH_{i,t-j} + b_{2jt} JL_{i,t-j} + b_{3jt} BH_{i,t-j} + b_{4jt} BL_{i,t-j} + b_{5jt} YH_{i,t-j} + b_{6jt} YL_{i,t-j} + e_{it}.$$

In Panel A, $YH_{i,t-j}$ ($YL_{i,t-j}$) is the 1-year high winner (loser) dummy that takes the value of 1 if the 1-year high measure for fund i is ranked in the top (bottom) 10% in month $t-j$, and zero otherwise. The 1-year high measure in month $t-j$ is the ratio of net asset value (NAV) in month $t-j$ to the maximum NAV achieved in months $t-j-12$ to $t-j$. The measures *JH*, *JL*, *BH*, and *BL* are defined similarly except that the *JH* (*JL*) indicates a winner (loser) by JT's ranking criterion, and *BH* (*BL*) indicates a winner (loser) by fund momentum factor loading, for the period between months $t-j-6$ and $t-j$. In Panel B, the regression dummy variables indicate whether a portfolio is ranked in the top or bottom 30%. The coefficient estimates of a given independent variable are averaged over j = 1, 2, 3 for 3-month holding periods, and j = 1, . . . , 6 for 6-month holding periods, and j = 1, …, 12 for 12-month holding periods. The numbers reported for the return in the tables are the time-series averages of these averages. They are in percent per month. The t-statistics (in parentheses) are calculated from the time series. To obtain risk-adjusted returns, I further run time series regressions of these averages (one for each average) on the contemporaneous Fama–French factor realizations to hedge out the factor exposure. The numbers reported for risk-adjusted returns are intercepts from these time-series regressions and their t-statistics are in parentheses. The sample includes all unique equity mutual funds in the CRSP mutual fund database.

Panel A: Extreme 10% Top and Bottom Portfolios

	Returns			Risk-adjusted Returns		
	3-month	6-month	12-month	3-month	6-month	12-month
Intercept	1.01	1.04	1.06	0.51	0.51	0.50
	(4.32)	(4.44)	(4.52)	(13.40)	(13.37)	(13.28)
JT winner dummy	0.27	0.29	0.23	0.27	0.27	0.19
	(2.68)	(3.09)	(2.68)	(3.12)	(3.64)	(3.11)
Beta4 winner dummy	0.11	0.12	0.12	0.18	0.19	0.18
	(1.26)	(1.40)	(1.36)	(2.65)	(2.84)	(2.80)
1-Year winner dummy	0.14	0.13	0.09	0.16	0.15	0.11
	(2.51)	(2.57)	(2.34)	(3.22)	(3.31)	(3.45)
JT loser dummy	-0.19	-0.16	-0.17	-0.20	-0.16	-0.17
	(-2.54)	(-2.48)	(-3.57)	(-2.58)	(-2.43)	(-3.63)
Beta4 loser dummy	-0.02	-0.02	-0.01	-0.12	-0.12	-0.11
	(-0.44)	(-0.37)	(-0.20)	(-2.50)	(-2.45)	(-2.36)
1-Year loser dummy	-0.09	-0.06	0.01	-0.14	-0.12	-0.06
	(-1.60)	(-1.16)	(0.11)	(-2.98)	(-2.89)	(-1.67)
JT winner - JT loser	0.47	0.45	0.39	0.47	0.44	0.36
	(2.91)	(3.16)	(3.38)	(3.03)	(3.23)	(3.59)
Beta4 winner - Beta4 loser	0.13	0.14	0.13	0.31	0.31	0.29
	(1.03)	(1.08)	(0.98)	(2.89)	(2.96)	(2.88)
1-Year winner - 1-Year loser	0.23	0.19	0.08	0.31	0.26	0.17
	(2.32)	(2.15)	(1.24)	(3.49)	(3.48)	(2.92)

Panel B: Extreme 30% Top and Bottom Portfolios						
	Returns			Risk-adjusted Returns		
	3-month	6-month	12-month	3-month	6-month	12-month
Intercept	0.99	1.01	1.02	0.50	0.50	0.49
	(4.28)	(4.38)	(4.44)	(12.69)	(12.61)	(12.63)
JT winner dummy	0.19	0.21	0.18	0.18	0.18	0.14
	(2.66)	(3.14)	(3.17)	(3.04)	(3.54)	(3.61)
Beta4 winner dummy	0.06	0.08	0.07	0.10	0.12	0.10
	(1.16)	(1.39)	(1.19)	(2.20)	(2.66)	(2.39)
1-Year winner dummy	0.08	0.06	0.04	0.09	0.07	0.05
	(2.37)	(2.05)	(1.83)	(2.83)	(2.65)	(2.67)
JT loser dummy	-0.12	-0.11	-0.10	-0.12	-0.12	-0.11
	(-2.52)	(-2.80)	(-3.18)	(-2.49)	(-2.92)	(-3.40)
Beta4 loser dummy	-0.01	-0.01	0.00	-0.06	-0.07	-0.05
	(-0.33)	(-0.18)	(0.12)	(-2.03)	(-2.26)	(-1.86)
1-Year loser dummy	-0.05	-0.02	0.01	-0.09	-0.06	-0.03
	(-1.21)	(-0.60)	(0.33)	(-2.57)	(-2.14)	(-1.20)
JT winner - JT loser	0.31	0.32	0.28	0.30	0.30	0.25
	(2.83)	(3.27)	(3.49)	(2.92)	(3.40)	(3.72)
Beta4 winner - Beta4 loser	0.07	0.08	0.06	0.16	0.19	0.15
	(0.93)	(1.00)	(0.74)	(2.39)	(2.76)	(2.39)
1-Year winner - 1-Year loser	0.13	0.08	0.03	0.18	0.13	0.08
	(1.92)	(1.44)	(0.64)	(3.00)	(2.72)	(2.13)

Table V
Profits from Momentum Strategies: Top and Bottom 10% of No-load Funds

The table reports average monthly returns from January 1973 to December 2004 for three different momentum investing strategies. Each month funds are ranked into deciles according to one of three criteria: (1) the prior 6-month return, (2) the fund momentum factor loading estimated from a 4-factor model over the prior 24 months, (3) the high NAV from the prior 12 months. The return to a strategy follows the method of Jegadeesh and Titman (1993) and in a given month is the average return from the portfolios formed in each of the prior months in the holding period. Panel A reports the time series mean of the cross-sectional mean returns for the top 10% and bottom 10% of funds for holding periods of 3, 6, and 12 months, respectively. Panel B reports the alpha from a time series regression of the cross-sectional mean return from the top and bottom decile portfolios on the Fama-French factors for holding periods of 3, 6, and 12 months, respectively. Funds with load fees are excluded from the sample, resulting in 2,845 unique funds comprising 15,830 fund-years. All returns are percent per month. *T*-statistics are in parenthesis.

Panel A: Fund Returns

	3-month			6-month			12-month		
Ranking criterion	Top	Bottom	Difference	Top	Bottom	Difference	Top	Bottom	Difference
Prior 6-month returns	1.46	0.76	0.70	1.49	0.84	0.65	1.42	0.90	0.52
	(5.07)	(2.77)	(3.10)	(5.17)	(3.17)	(3.23)	(4.94)	(3.71)	(3.24)
Momentum factor loading	1.18	0.97	0.21	1.22	1.03	0.19	1.23	1.05	0.18
	(3.78)	(4.11)	(1.14)	(3.93)	(4.42)	(1.05)	(4.00)	(4.60)	(1.00)
Prior 1-year high NAV	1.34	0.78	0.56	1.35	0.89	0.46	1.30	1.02	0.28
	(5.83)	(2.65)	(3.26)	(5.81)	(3.10)	(2.97)	(5.59)	(3.73)	(2.41)

Panel B: 3-factor Alphas

	3-month			6-month			12-month		
Ranking criterion	Top	Bottom	Difference	Top	Bottom	Difference	Top	Bottom	Difference
Prior 6-month returns	0.43	-0.27	0.70	0.41	-0.22	0.64	0.32	-0.19	0.51
	(3.49)	(-2.22)	(3.17)	(3.73)	(-1.99)	(3.23)	(3.42)	(-2.36)	(3.47)
Momentum factor loading	0.24	-0.18	0.41	0.23	-0.14	0.37	0.20	-0.15	0.34
	(2.31)	(-2.28)	(2.89)	(2.27)	(-1.87)	(2.65)	(2.07)	(-2.18)	(2.67)
Prior 1-year high NAV	0.34	-0.31	0.65	0.31	-0.25	0.56	0.23	-0.15	0.38
	(3.70)	(-2.91)	(3.92)	(3.78)	(-2.50)	(3.71)	(3.54)	(-1.85)	(3.31)

Table VI
Profits from Momentum Strategies: Top and Bottom 30% of No-load Funds

The table reports average monthly returns from January 1973 to December 2004 for three different momentum investing strategies. Each month funds are ranked into deciles according to one of three criteria: (1) the prior 6-month return, (2) the fund momentum factor loading estimated from a 4-factor model over the prior 24 months, (3) the high NAV from the prior 12 months. The return to a strategy follows the method of Jegadeesh and Titman (1993) and in a given month is the average return from the portfolios formed in each of the prior months in the holding period. Panel A reports the time series mean of the cross-sectional mean returns for the top 30% and bottom 30% of funds for holding periods of 3, 6, and 12 months, respectively. Panel B reports the alpha from a time series regression of the cross-sectional mean return from the top and bottom decile portfolios on the Fama-French factors for holding periods of 3, 6, and 12 months, respectively. Funds with load fees are excluded from the sample, resulting in 2,845 unique funds comprising 15,830 fund-years. All returns are percent per month. *T*-statistics are in parenthesis.

Panel A: Fund Returns

	3-month			6-month			12-month		
Ranking criterion	Top	Bottom	Difference	Top	Bottom	Difference	Top	Bottom	Difference
Prior 6-month returns	1.30	0.83	0.47	1.33	0.89	0.44	1.29	0.95	0.34
	(5.06)	(3.29)	(3.21)	(5.16)	(3.59)	(3.38)	(5.00)	(4.05)	(3.29)
Momentum factor loading	1.10	0.99	0.11	1.14	1.04	0.11	1.15	1.07	0.08
	(3.99)	(4.39)	(0.89)	(4.12)	(4.61)	(0.86)	(4.16)	(4.81)	(0.67)
Prior 1-year high NAV	1.23	0.89	0.34	1.25	0.96	0.29	1.22	1.02	0.19
	(5.34)	(3.33)	(2.78)	(5.37)	(3.64)	(2.66)	(5.21)	(4.05)	(2.45)

Panel B: 3-factor Alphas

	3-month			6-month			12-month		
Ranking criterion	Top	Bottom	Difference	Top	Bottom	Difference	Top	Bottom	Difference
Prior 6-month returns	0.27	-0.19	0.46	0.26	-0.17	0.44	0.20	-0.14	0.34
	(3.27)	(-2.41)	(3.27)	(3.49)	(-2.30)	(3.43)	(3.13)	(-2.30)	(3.52)
Momentum factor loading	0.14	-0.10	0.25	0.13	-0.09	0.22	0.11	-0.08	0.18
	(2.17)	(-1.80)	(2.68)	(2.06)	(-1.57)	(2.47)	(1.67)	(-1.54)	(2.23)
Prior 1-year high NAV	0.21	-0.17	0.39	0.20	-0.14	0.34	0.14	-0.10	0.24
	(3.12)	(-2.27)	(3.21)	(3.23)	(-1.99)	(3.18)	(2.84)	(-1.71)	(3.07)

Table VII
Comparison of Momentum Trading Strategies: No-load Funds

The sample is limited to no-load funds, resulting in 2,845 unique funds comprising 15,830 fund-years. Each month from January 1973 to December 2004, either 3 (j = 1, 2, 3), 6 (j = 1, …, 6), or 12 (j = 1, …, 12) cross-sectional regressions of the following form are estimated for investment holding periods of 3, 6, and 12 months, respectively:

$$R_{it} = b_{0jt} + b_{1jt}JH_{i,t-j} + b_{2jt}JL_{i,t-j} + b_{3jt}BH_{i,t-j} + b_{4jt}BL_{i,t-j} + b_{5jt}YH_{i,t-j} + b_{6jt}YL_{i,t-j} + e_{it}.$$

In Panel A, $YH_{i,t-j}$ ($YL_{i,t-j}$) is the 1-year high winner (loser) dummy that takes the value of 1 if the 1-year high measure for fund i is ranked in the top (bottom) 10% in month $t-j$, and zero otherwise. The 1-year high measure in month $t-j$ is the ratio of net asset value (NAV) in month $t-j$ to the maximum NAV achieved in months $t-j-12$ to $t-j$. The measures *JH*, *JL*, *BH*, and *BL* are defined similarly except that the *JH* (*JL*) indicates a winner (loser) by JT's ranking criterion, and *BH* (*BL*) indicates a winner (loser) by fund momentum factor loading, for the period between months $t-j-6$ and $t-j$. In Panel B, the regression dummy variables indicate whether a portfolio is ranked in the top or bottom 30%. The coefficient estimates of a given independent variable are averaged over j = 1, 2, 3 for 3-month holding periods, and j = 1, . . . , 6 for 6-month holding periods, and j = 1, …, 12 for 12-month holding periods. The numbers reported for the return in the tables are the time-series averages of these averages. They are in percent per month. The *t*-statistics (in parentheses) are calculated from the time series. To obtain risk-adjusted returns, I further run time series regressions of these averages (one for each average) on the contemporaneous Fama–French factor realizations to hedge out the factor exposure. The numbers reported for risk-adjusted returns are intercepts from these time-series regressions and their *t*-statistics are in parentheses.

Panel A: Extreme 10% Top and Bottom Portfolios						
	Returns			Risk-adjusted Returns		
	3-month	6-month	12-month	3-month	6-month	12-month
Intercept	1.15	1.13	1.15	0.50	0.50	0.50
	(4.74)	(4.64)	(4.65)	(12.68)	(12.40)	(12.38)
JT winner dummy	0.31	0.32	0.22	0.27	0.29	0.21
	(2.60)	(2.85)	(2.07)	(2.78)	(3.32)	(2.76)
Beta4 winner dummy	0.09	0.09	0.10	0.13	0.13	0.13
	(0.86)	(0.89)	(1.01)	(1.68)	(1.70)	(1.86)
1-Year winner dummy	0.16	0.14	0.09	0.17	0.15	0.11
	(2.55)	(2.45)	(2.10)	(2.84)	(2.87)	(2.93)
JT loser dummy	-0.23	-0.22	-0.20	-0.17	-0.17	-0.18
	(-2.67)	(-2.98)	(-3.71)	(-1.89)	(-2.20)	(-3.32)
Beta4 loser dummy	-0.07	-0.04	-0.05	-0.15	-0.13	-0.14
	(-1.05)	(-0.66)	(-0.78)	(-2.68)	(-2.29)	(-2.69)
1-Year loser dummy	-0.15	-0.12	-0.04	-0.20	-0.17	-0.07
	(-2.48)	(-2.30)	(-0.75)	(-3.54)	(-3.62)	(-1.87)
JT winner - JT loser	0.54	0.55	0.41	0.44	0.46	0.39
	(2.94)	(3.24)	(2.97)	(2.56)	(3.03)	(3.32)
Beta4 winner - Beta4 loser	0.15	0.13	0.15	0.28	0.25	0.27
	(1.03)	(0.86)	(0.99)	(2.42)	(2.21)	(2.47)
1-Year winner - 1-Year loser	0.31	0.26	0.12	0.37	0.32	0.18
	(2.91)	(2.79)	(1.63)	(3.67)	(3.71)	(2.76)

Panel B: Extreme 30% Top and Bottom Portfolios						
	Returns			Risk-adjusted Returns		
	3-month	6-month	12-month	3-month	6-month	12-month
Intercept	1.01	1.03	1.06	0.49	0.48	0.49
	(4.30)	(4.40)	(4.53)	(11.21)	(11.33)	(12.21)
JT winner dummy	0.24	0.26	0.22	0.22	0.23	0.17
	(3.10)	(3.67)	(3.49)	(3.49)	(4.03)	(3.81)
Beta4 winner dummy	0.05	0.06	0.05	0.09	0.11	0.09
	(0.83)	(1.04)	(0.82)	(1.82)	(2.13)	(1.82)
1-Year winner dummy	0.07	0.05	0.02	0.07	0.07	0.04
	(1.65)	(1.46)	(0.88)	(1.98)	(2.15)	(1.82)
JT loser dummy	-0.14	-0.14	-0.12	-0.13	-0.13	-0.11
	(-2.82)	(-3.24)	(-3.62)	(-2.43)	(-2.94)	(-3.31)
Beta4 loser dummy	-0.06	-0.04	-0.03	-0.08	-0.08	-0.07
	(-1.46)	(-1.10)	(-0.86)	(-2.34)	(-2.45)	(-2.46)
1-Year loser dummy	-0.04	-0.01	0.02	-0.09	-0.05	-0.03
	(-0.89)	(-0.19)	(0.41)	(-1.95)	(-1.40)	(-1.11)
JT winner - JT loser	0.38	0.40	0.33	0.35	0.36	0.28
	(3.31)	(3.86)	(3.90)	(3.28)	(3.82)	(3.93)
Beta4 winner - Beta4 loser	0.10	0.10	0.08	0.18	0.19	0.16
	(1.25)	(1.19)	(0.91)	(2.48)	(2.65)	(2.38)
1-Year winner - 1-Year loser	0.11	0.06	0.01	0.16	0.12	0.08
	(1.44)	(0.90)	(0.15)	(2.33)	(2.09)	(1.69)

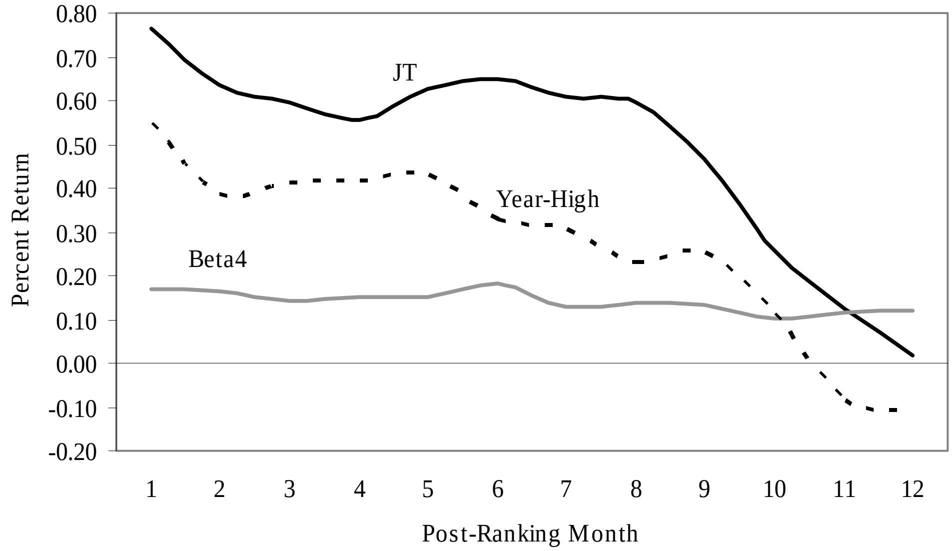
Table VIII
Determinants of Fund Cash Flows

This table presents the coefficients from regressions of monthly normalized cash flow for a fund against the fund's total return over the previous six months, the fund momentum loading, nearness to the year high NAV, the logarithm of total net assets, the normalized cash flow during the prior month, turnover, expense ratio, and maximum total load fees. The normalized cash flow for a fund during a month is computed as the dollar monthly cash flow for the fund divided by the total net assets (TNA) at the beginning of the month. Nearness to the one-year high NAV is $NAV_{t-1} \div high_{t-1}$. The reported coefficients are averages of 168 monthly cross-sectional regressions for all funds from January 1991 to December 2004. *T*-statistics based on a Newey-West covariance matrix are reported in parenthesis. The cross-sectional R^2 is computed as $\left[Var\left(\overline{C}_i\right)-Var\left(\overline{\varepsilon}_i\right)\right]/Var\left(\overline{C}_i\right)$, where $\overline{\varepsilon}_i$ is the average cross-sectional residual for fund i, $\overline{C}_i$ is the average percentage net cash flow for fund i, all variances are cross-sectional, and variables with bars over them denote time-series averages.

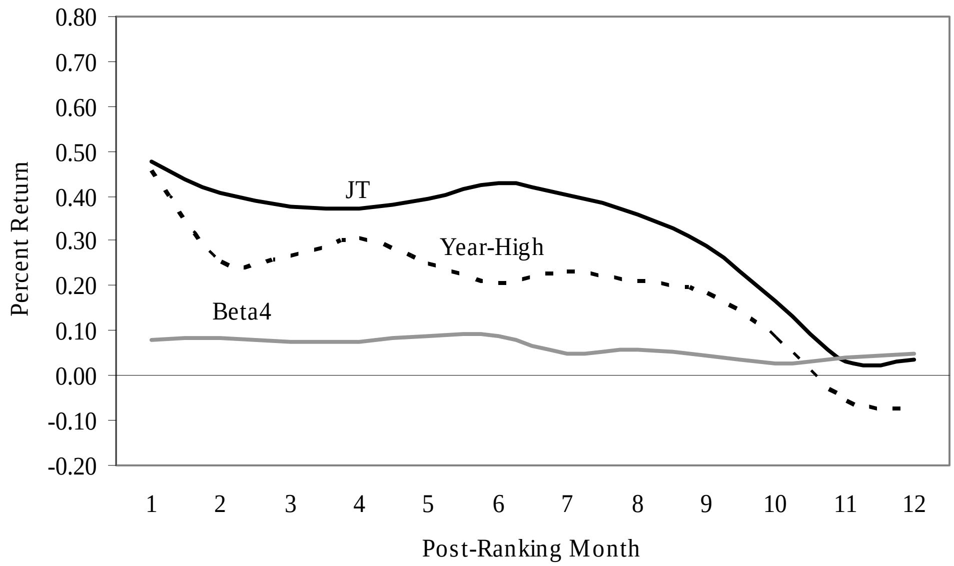
Explanatory Variables	Model				
	I	II	III	IV	V
Intercept	-0.01 (-3.77)	-0.04 (-4.64)	-0.04 (-5.04)	-0.03 (-3.91)	-0.03 (-3.77)
Lagged six-month total return	1.23 (12.51)	1.08 (10.47)	1.14 (10.43)	0.98 (10.99)	0.99 (10.35)
Momentum factor loading	0.003 (0.92)		0.003 (1.03)	0.003 (1.04)	-0.001 (-0.23)
Nearness to the one-year high *NAV*		0.033 (4.09)	0.033 (4.37)	0.032 (4.01)	0.036 (4.20)
Logarithm of TNA_{t-1}				-0.001 (-4.27)	-0.001 (-4.97)
Previous month's net cash flow				0.11 (5.12)	0.11 (5.14)
Turnover					0.001 (1.83)
Expense ratio					-0.19 (-2.14)
Maximum total load					0.000 (-0.03)
Cross-sectional R^2	0.084	0.088	0.095	0.221	0.231

Figure 1

(A) One-Month Raw Returns: 10% Long-Short Strategy



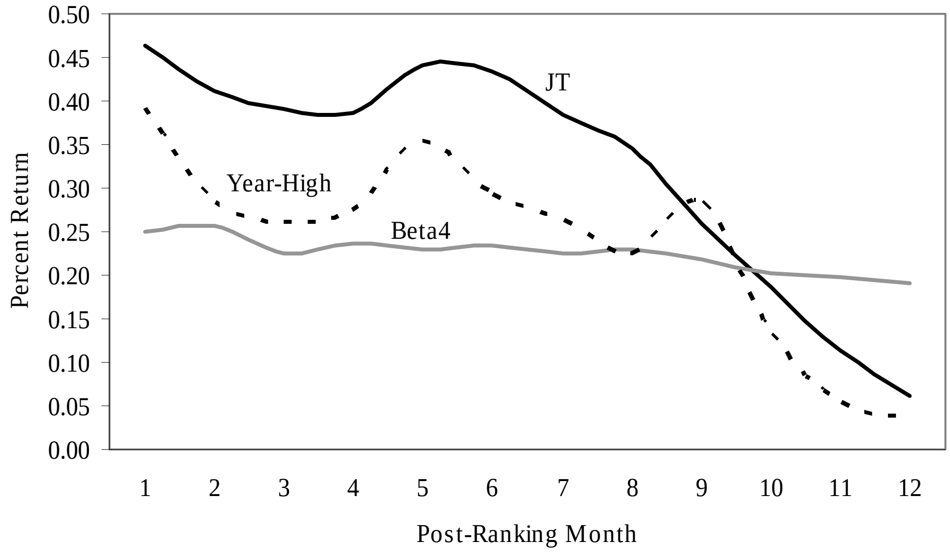
(B) One-Month Raw Returns: 30% Long-Short Strategy



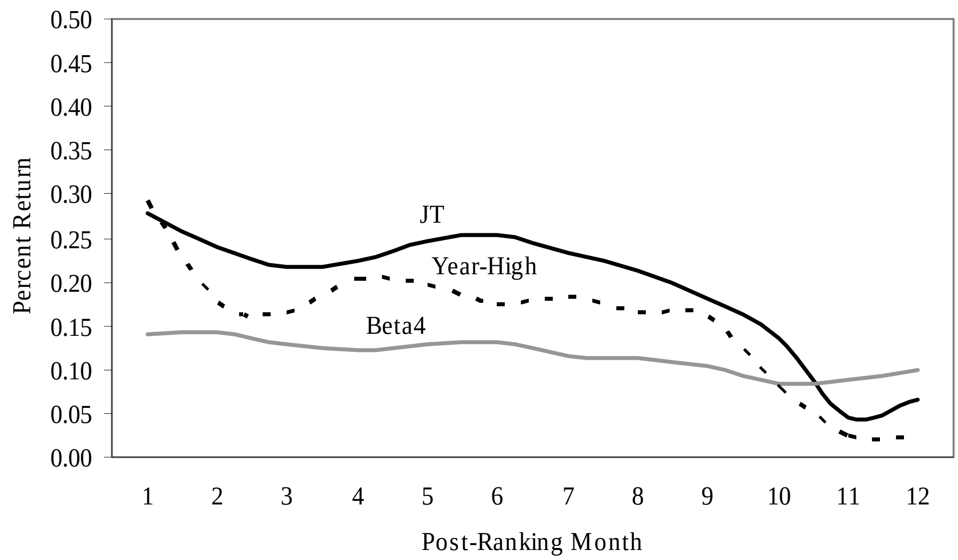
Funds are ranked into deciles according to either the past six-month return (JT), fund momentum loading (Beta4), or nearness to the high NAV (Year-High). The one-month holding period returns over a twelve-month horizon following portfolio formation are displayed. **(A)** The figure shows raw monthly returns to a strategy which buys the top 10% of funds and sells the bottom 10% of funds according to each of the three ranking criterion. **(B)** The figure shows raw monthly returns to a strategy which buys the top 30% of funds and sells the bottom 30% of funds according to each of the three ranking criterion.

Figure 2

(A) One-Month Alphas: Top 10% Portfolio



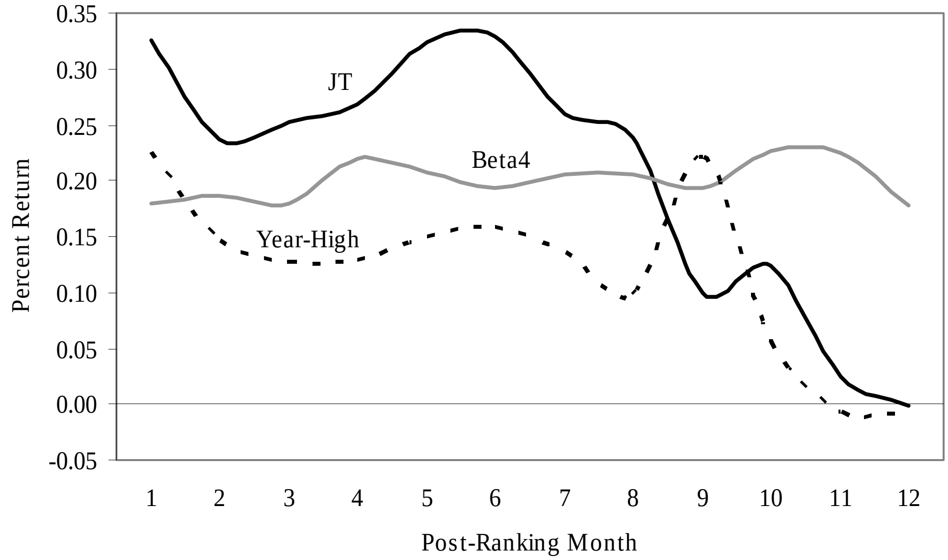
(B) One-Month Alphas: Top 30% Portfolio



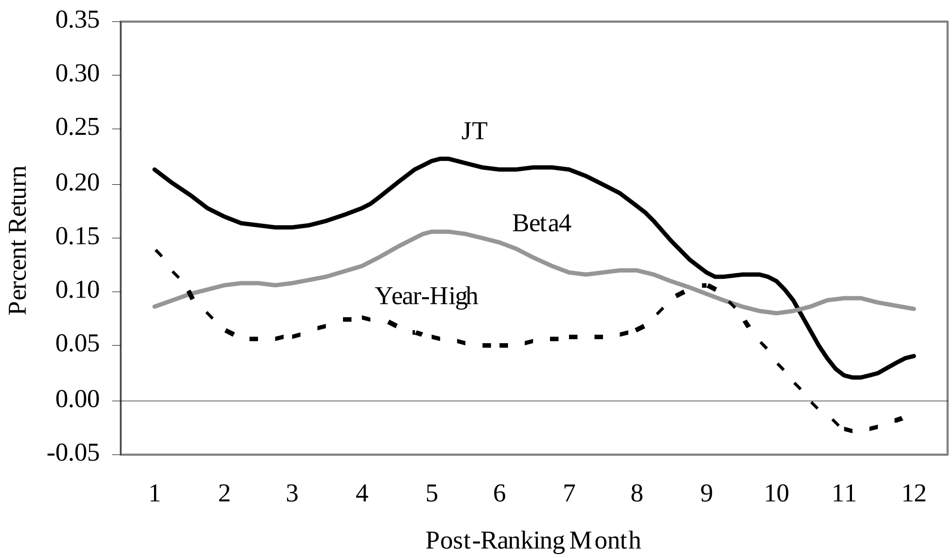
Funds are ranked into deciles according to either the past six-month return (JT), fund momentum loading (Beta4), or nearness to the high NAV (Year-High). The one-month holding period returns over a twelve-month horizon following portfolio formation are displayed. The figure shows monthly returns that have been adjusted for market risk and style to a strategy which **(A)** buys the top 10% of funds, or **(B)** buys the top 30% of funds, according to each of the three ranking criterion. The reported returns are the alphas obtained by regressing the time series of portfolio returns on the contemporaneous Fama-French factors.

Figure 3

(A) One-Month Hedged Alphas: Top 10% Portfolio



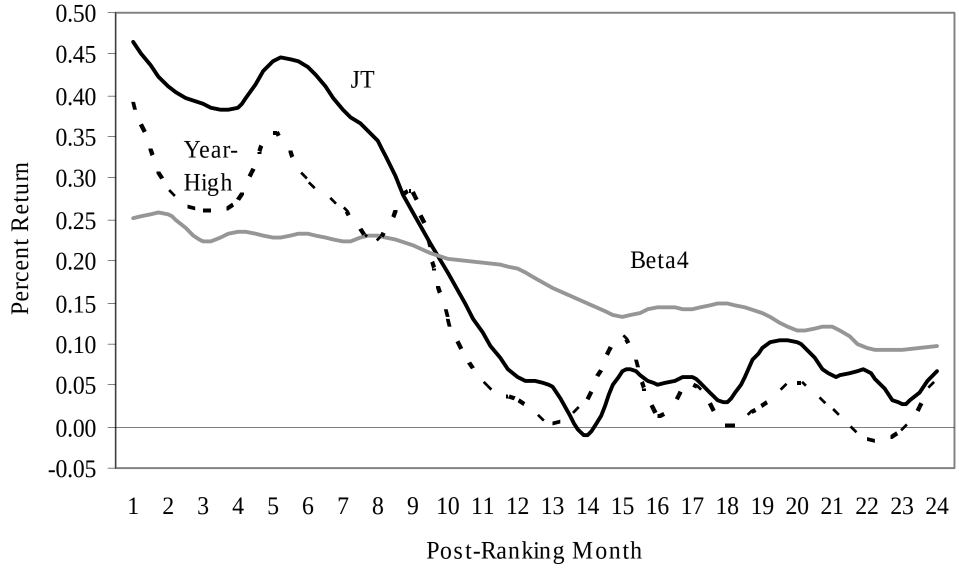
(B) One-Month Hedged Alphas: Top 30% Portfolio



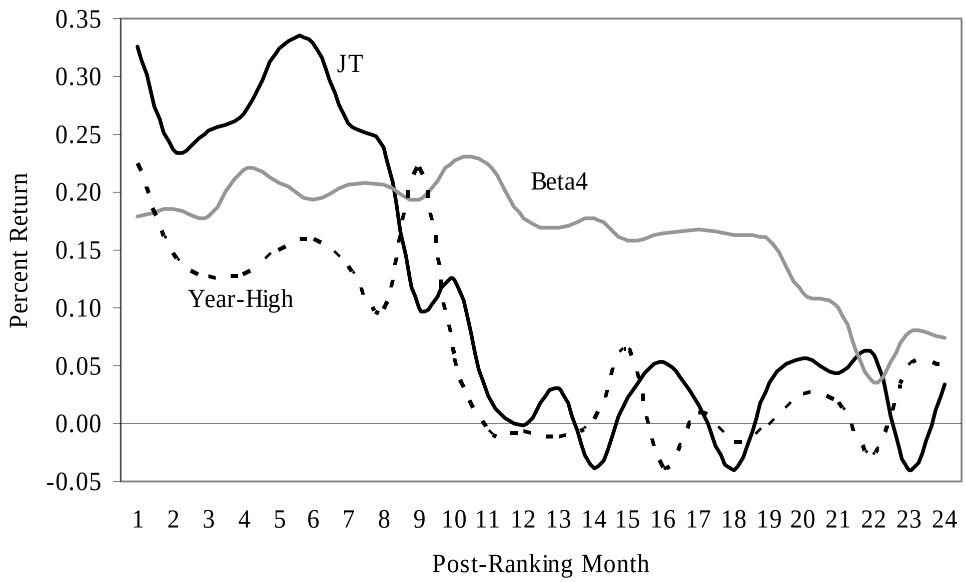
Portfolios are ranked according to either the past six-month return (JT), fund momentum loading (Beta4), or nearness to the high NAV (Year-High). To estimate returns to each strategy while hedging out the effects of the other two strategies, each month fund returns are regressed on a set of six dummy variables which indicate whether the fund ranked in the top or bottom portfolio in the formation month according to each of the three measures. The time series of resulting coefficients for the winners of each strategy is then regressed on the contemporaneous Fama-French factors to adjust for risk. This procedure is repeated for each month after portfolio formation, up to a twelve month horizon. **(A)** The figure shows the one-month holding period returns for the top 10% of funds by each measure over a twelve-month horizon following portfolio formation. **(B)** The figure shows the one-month holding period returns for the top 30% of funds by each measure over a twelve-month horizon following portfolio formation.

Figure 4

(A) Long-Term One-Month Alphas: Top 10% Portfolio



(B) Long-Term One-Month Hedged Alphas: Top 10% Portfolio



Portfolios are ranked according to either the past six-month return (JT), fund momentum loading (Beta4), or nearness to the high NAV (Year-High). This procedure is repeated for each month after portfolio formation, up to a 24-month horizon. **(A)** The figure shows the one-month holding period returns for the top 10% of funds by each measure over a 24-month horizon following portfolio formation. The reported returns are the alphas obtained by regressing the time series of portfolio returns on the contemporaneous Fama-French factors. **(B)** The figure shows the one-month holding period returns for the top 10% of funds by each measure over a 24-month horizon following portfolio formation. To estimate returns to each strategy while hedging out the effects of the other two strategies, each month fund returns are regressed on a set of six dummy variables which indicate whether the fund ranked in the top or bottom portfolio in the formation month according to each of the three measures. The time series of resulting coefficients for the winners of each strategy is then regressed on the contemporaneous Fama-French factors to adjust for risk. (Figure (A) are the stand-alone strategy alphas, and figure (B) are the hedged alphas.)

Appendix Table A1
Profits from Momentum Strategies: Fund-by-Fund Alphas

The table reports average monthly returns adjusted for market risk and style from January 1973 to December 2004 for three different momentum investing strategies. A risk-adjusted return (alpha) is first computed for each fund in each month from factor realizations and Fama-French (1993) factor loadings estimated over the prior 36 months. Then each month funds are ranked into deciles according to one of three criteria: (1) the prior 6-month return, (2) the fund momentum factor loading estimated from a 4-factor model over the prior 24 months, (3) the high NAV from the prior 12 months. The return to a strategy in a given month is the average alpha from the portfolios formed in each of the prior months in the holding period. Panel A reports the time series mean of the cross-sectional mean alphas for the top 10% and bottom 10% of funds for holding periods of 3, 6, and 12 months, respectively. Panel B reports the time series mean of the cross-sectional mean alphas for the top 30% and bottom 30% of funds for holding periods of 3, 6, and 12 months, respectively. The sample includes all unique equity mutual funds in the CRSP mutual fund database. All returns are percent per month. *T*-statistics are in parenthesis.

Panel A: Top & Bottom 10%

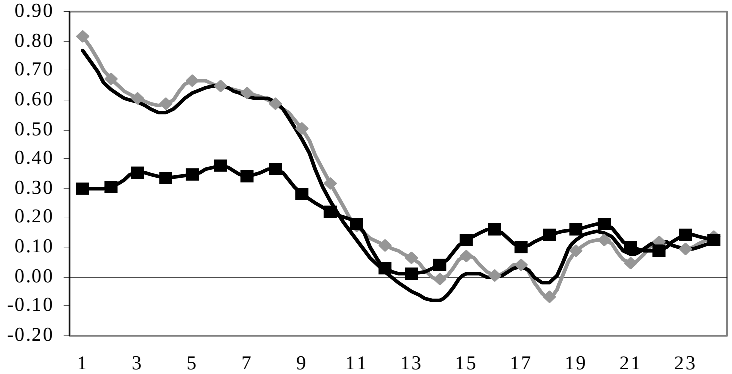
	3-month			6-month			12-month		
Ranking criterion	Top	Bottom	Difference	Top	Bottom	Difference	Top	Bottom	Difference
Prior 6-month returns	0.21	-0.11	0.32	0.23	-0.11	0.34	0.19	-0.12	0.30
	(3.86)	(-2.23)	(4.53)	(4.38)	(-2.31)	(5.27)	(3.75)	(-2.89)	(5.60)
Momentum factor loading	0.22	-0.10	0.32	0.22	-0.09	0.31	0.18	-0.10	0.28
	(2.87)	(-2.16)	(3.30)	(2.84)	(-2.11)	(3.30)	(2.51)	(-2.40)	(3.20)
Prior 1-year high NAV	0.14	-0.05	0.19	0.14	-0.03	0.18	0.12	-0.04	0.16
	(3.82)	(-0.86)	(3.13)	(4.27)	(-0.63)	(3.22)	(3.75)	(-0.80)	(3.39)

Panel A: Top & Bottom 30%

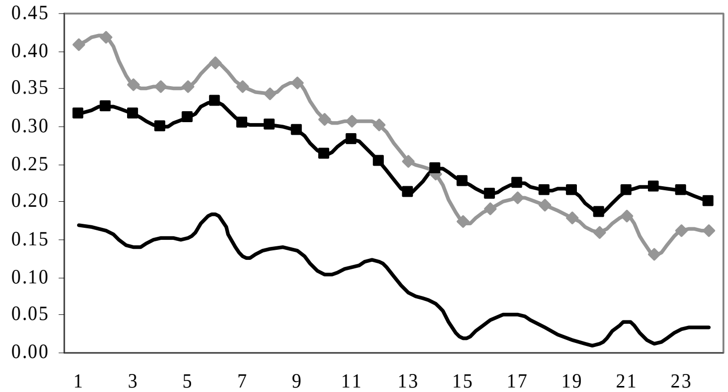
	3-month			6-month			12-month		
Ranking criterion	Top	Bottom	Difference	Top	Bottom	Difference	Top	Bottom	Difference
Prior 6-month returns	0.14	-0.06	0.20	0.15	-0.06	0.21	0.12	-0.07	0.19
	(3.45)	(-1.57)	(4.19)	(3.72)	(-1.72)	(4.92)	(3.17)	(-2.14)	(5.32)
Momentum factor loading	0.14	-0.07	0.21	0.14	-0.06	0.20	0.11	-0.07	0.18
	(2.69)	(-2.00)	(3.40)	(2.64)	(-1.85)	(3.32)	(2.20)	(-2.02)	(3.07)
Prior 1-year high NAV	0.10	-0.03	0.14	0.10	-0.03	0.13	0.08	-0.04	0.12
	(3.37)	(-0.81)	(3.32)	(3.37)	(-0.67)	(3.37)	(2.81)	(-0.97)	(3.70)

Appendix Figure A1

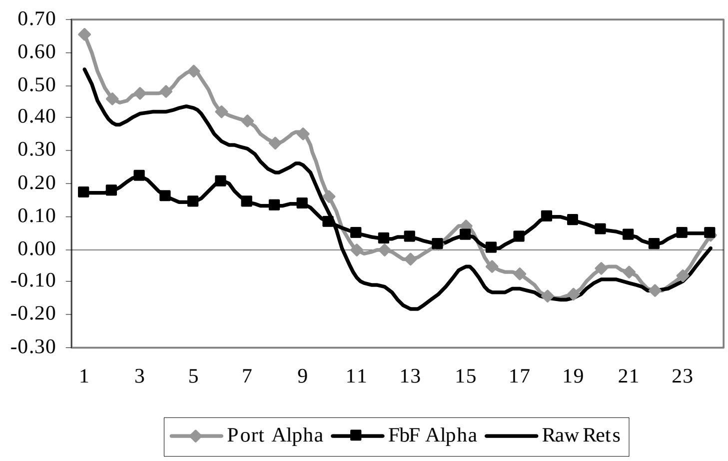
(A) Portfolio versus Fund-by-Fund Alphas: JT Strategy



(B) Portfolio versus Fund-by-Fund Alphas: Beta4 Strategy

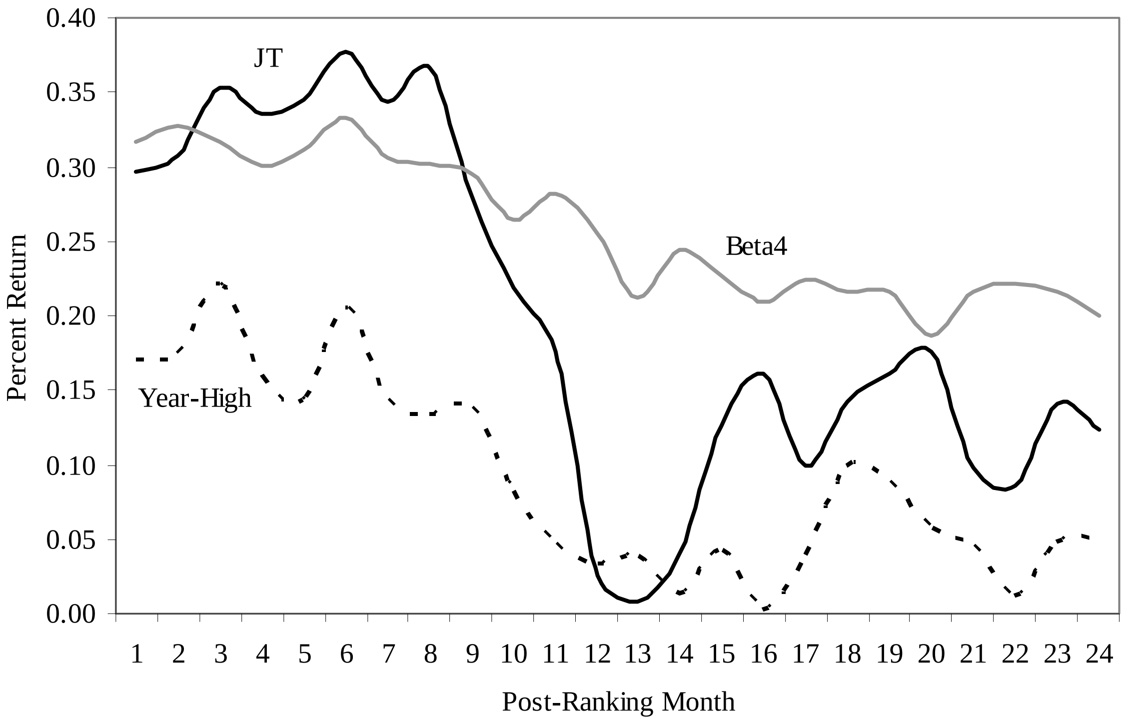


(C) Portfolio versus Fund-by-Fund Alphas: 1-Year High Strategy



The figure shows the one-month holding period returns for a strategy which buys the top 10% of funds and sells the bottom 10% of funds by each measure over a 24-month horizon following portfolio formation. The reported returns are average raw returns (Raw Rets), the portfolio alphas (Port Alpha) obtained by regressing the time series of portfolio returns on the contemporaneous Fama-French factors, and the average fund-by-fund alphas (FbF Alpha) computed for each fund in each month from factor loadings and factor realizations.

Appendix Figure A2
One-Month Fund-by-Fund Alphas



The figure shows the one-month holding period returns for a strategy which buys the top 10% of funds and sells the bottom 10% of funds by each measure over a 24-month horizon following portfolio formation. The reported returns are the average fund-by-fund alphas computed for each fund in each month from factor loadings and factor realizations.