Fund raw return and future performance

André de Souza*

30 September 2017

Abstract

Mutual funds with low raw return do better in the future than funds with high raw return. This is because the stocks sold by low-raw-return funds have their prices pushed down and subsequently outperform. I argue that funds with low raw return suffer "unsophisticated" outflows, forcing them to make unoptimal sales of stocks whose prices then quickly revert. My results have implications for the debate on performance persistence.

Keywords: Mutual funds, raw return, performance persistence. *JEL:* G23

*Department of Economics and Finance, St John's University, and Department of Finance, NYU Stern. Email: desouzab@stjohns.edu. This paper is based in part on a chapter of my dissertation at NYU Stern School of Business. I thank my committee: Marty Gruber, Marcin Kacperczyk, Anthony Lynch (chair) and David Yermack, and Justin Birru, Richard Carrizosa, Pete Kyle, Dong Lou, Jonathan Reuter, Johnathan Wang, Shaojun Zhang, Ken Zhong (Triple Crown discussant), and seminar participants at NYU Stern, Fordham University, University of Texas at Dallas, University of Toronto, Aalto University School of Economics, BI Nydalen, University of New South Wales, Case Western Reserve University, the Financial Markets Workshop at the Rising Star Conference 2013, the Financial Management Association 2013 Conference, the Triple Crown 2014 Conference, and the University of Oklahoma for comments. I also thank Lance Young for giving me PIN and Adjusted-PIN data. Some of this work was supported by a Fordham University summer research grant. An earlier version of this paper was circulated under the title "A mispricing-based explanation of how flow affects mutual fund performance". All errors remain my responsibility.

1 Introduction

I study whether a mutual fund's raw return affects its future stockpicking performance, as measured by alpha, at the annual horizon. By fund raw return, I mean the return on the fund over the past twelve months, unadjusted for risk. By alpha, I mean the Carhart alpha over the next twelve months. I show that raw return is negatively related to future alpha, and present evidence for a channel through which this effect occurs.

Ex ante, why might one suspect there is such a relation? A first step is understanding why some funds have high raw return, and some have low. Controlling for current alpha, funds with higher raw returns are those that have had favorable factor realizations. This may be because they were lucky, or because they have some dimension of skill (e.g., factor-timing) that is not picked up by the current alpha. For such skill to affect future alpha, controlling for current alpha, its effects must (a) not be captured by current alpha, but must simultaneously (b) affect future alpha. It is hard to see how this might happen.

On the other hand, suppose that the funds that had high raw return were lucky to some extent. Previous work (Gruber (1996), Sirri and Tufano (1998)) shows that, controlling for alpha, fund investors chase raw return, even though it might be uninformative of skill. The literature also argues that flows may drive down future performance (Berk and Green, 2004). Putting these arguments together, funds with high raw return receive more flow than those with low raw return, and should therefore underperform in the future.

If the intent is to show that flow drives down future performance, why not directly study the effect of flow instead? Even if flow did affect future performance negatively, the relationship might not be observable in the data. The reason is that flows are not allocated randomly. There is a selection effect – the funds that get high flow are the funds that investors thought were more skilled. If fund investors flows are, on average, "smart money" (Gruber (1996), Zheng (1999)), then funds which get large flows are likely to be more skilled than those that do not. The two effects – the positive selection effect and the hypothesized negative effect of flow – would cancel out, leading to there being no observed relation between flow and future alpha[1].

But raw return might still be related to future alpha through the flow channel. High raw-return funds have high flows, because some fund investors chase raw return. To the extent that having

[1]This is exactly what happens in Berk and Green (2004). Flows are assumed to reduce future fund performance, but investors in that model are rational, and only move flows to funds that would have outperformed had they not received flow. Reuter and Zitzewitz (2013) observe that consequently, in that model, fund performance is completely unpredictable: funds receive more inflow when they are expected to perform better, and more outflow when they are expected to perform worse, thereby eliminating all predictability. They search, as I do, for a source of variation in fund flows that is unrelated to fund skill. They use the discontinuity in flows around Morningstar star ranking cutoffs to estimate the causal effect of flows on fund performance.

high raw return is a matter of luck, those investors are not smart[2], and so these high flows are less likely to imply fund skill. Compare high flow funds and high raw return funds. The high flow funds have high flows, but, if the average fund investor is smart, also have high skill. High raw return funds, on the other hand, have high flows, but if those flows came from unsophisticated investors, there would be no implication for fund skill. One might then think of raw return as a proxy for "unsophisticated flow". In sum, if (a) flow does affect future performance negatively, and (b) raw return contains a component of luck, I should find a negative relation between raw return and future performance.

Consistent with this intuition, I find that a fund's raw return over one year is significantly negatively related to its alpha over the subsequent year, controlling for past alpha. In a portfolio context, among funds with high past alpha, funds with high raw return have an insignificantly negative alpha over the next year, while funds with low raw return have a significant and positive alpha of 2.6%, net of expenses. Among funds with low past alpha, funds with low raw return have an insignificantly negative future alpha, but funds with high raw return have a significantly negative alpha of -2.11%. In a Fama-MacBeth regression, a one standard deviation increase in raw return in one year reduces alpha by 10 bp/month in the next year. I ensure that this finding is not driven by incubation bias (Evans, 2010), time-varying factor risk premia, measurement error in the alphas, or hitherto-undocumented momentum effects.

Given that raw return – my proxy for unsophisticated flow – is negatively related to future fund alpha, I search for the mechanism through which this effect occurs. A straightforward way in which flow might affect future fund performance is if it affected stock prices. Prior research (Lou, 2012) finds that funds respond to flow by scaling their positions up or down[3]. Such trades are unlikely to contain information (Alexander et al. (2007)), but may, in aggregate, move stock prices. Therefore, stocks in which positive-flow funds have increased their positions will likely have gone up in price on no information, and so would be expected to underperform. Because flows chase performance, these stocks are likely to be the ones held by well-performing funds, and the reversal will result in these funds underperforming. Conversely, stocks sold by funds with outflows should outperform in the future, improving the performance of funds that have done badly this period. In either case, the reversal of stock price movements caused by flow may lead to a negative relation between flow and future performance.

[2]Controlling for raw return and Morningstar ratings, Del Guercio and Tkac (2002) find risk-adjusted performance is not a significant determinant of flows, suggesting that investors use simple signals in making investment decisions. Del Guercio and Reuter (2014) show that the flow response to raw return is stronger for broker-sold funds than for funds sold directly to investors. Combined with their result that fund underperformance is confined to broker-sold funds, this again suggests that this flow sensitivity is due to relative unsophistication.

[3]Pollet and Wilson (2008) show funds receiving flows do not increase the number of stocks they hold.

This argument is intuitive and plausible. But Lou (2012) finds no evidence for reversal in price movements due to flow in the year following the flow. Instead, he finds evidence for continuation from one quarter to the next, and only finds reversal at horizons longer than a year. However, price movements due to *unsophisticated* flows may well reverse more quickly than movements due to flows in general.

Accordingly, I construct measures of how much a fund's current portfolio has been (a) bought up by funds with high raw return (high unsophisticated flow) (b) sold by funds with low raw return (low unsophisticated flow). I find that the sales measure is strongly related to future fund performance: funds whose current portfolios have been pushed down in price by sales do better in the future. The sales measure subsumes the predictive power of the fund's own raw return. This means that raw return predicts future fund performance because it proxies for the extent to which a fund's current portfolio has been pushed down in price.

In contrast, the buys measure is not significantly related to future performance.

What are the implications of my findings? Showing that a proxy for flow is negatively related to future performance at the annual horizon is important because it provides a reason why we do not observe performance persistence from one year to the next[4]. Specifically, funds which do well receive flow and this drives down their future performance. Funds which do badly suffer outflows and this improves subsequent performance. In both cases, the hypothesized negative effect of flows on future performance leads to a lack of persistence. This is a version of the argument advanced by Berk and Green (2004)[5]. My base result: that funds with high raw returns do badly and those with low raw returns do well, appears to confirm this intuition.

However, when I dig deeper, I find that the mechanism driving this effect is one-sided. Sales push prices down and improve performance next period, but buys have no impact. Therefore, this mechanism can only increase future fund performance. So it can explain why funds which have done badly do not continue to do badly. But this effect is not confined to poor performers; it also affects some funds which have done well[6]. It helps these funds to continue to do well, and *strengthens* the appearance of performance persistence among high-alpha funds. In the absence of this effect, outperforming funds would exhibit *even less* performance persistence than they actually do. Consequently, my results deepen the mystery of the observed lack of persistent outperformance.

[4]Carhart (1997). Performance persistence has been demonstrated at shorter horizons (Bollen and Busse, 2005), in subsets of the mutual fund universe (Da et al., 2011; Cremers and Petajisto, 2009), and at specific points in the business cycle (Glode et al., 2012).

[5]Lynch and Musto (2003) make another argument for the lack of persistence among poor performers: they not continue to do badly because they change their strategies after observing their own poor performance.

[6]Though these funds may not have been forced by low flow to sell stocks themselves, they may be holding stocks whose prices have been moved by the sales of other funds suffering relatively low flows.

2 Relation to the literature

This paper unites two streams of literature. First, in showing that a proxy for flow is negatively related to future performance and in describing one channel through which this occurs, it contributes to the literature which argues that flows may be responsible for the observed lack of fund performance persistence (Berk and Green, 2004). Some of these papers examine the relation between flow and performance directly (Reuter and Zitzewitz (2013), Berk and Tonks (2007)). Others (Edelen et al. (2007), Chen et al. (2004), Yan (2008), Elton et al. (2012)) provide evidence of diseconomies of scale in fund management, since this is the mechanism through which flows affect performance in the model of Berk and Green (2004), by changing fund size. By and large, these papers provide compelling evidence that scale diseconomies do exist. However, it is not evident that the changes in a single fund's size due to flow over short horizons are comparable to the differences in size across funds in cross-section – it is not clear that "diseconomies of scale in time-series" are sufficient to eliminate performance persistence. My paper offers an alternative mechanism through which flows affect fund performance – through stock prices rather than affecting anything about the fund itself.

A second body of work to which this paper contributes is that showing that trades made by funds with flows affect stock prices. While the focus of those papers is on subsequent *stock* performance at long horizons (Frazzini and Lamont, 2008) or in extreme flow events (Coval and Stafford, 2007), this paper shows that flows which are not necessarily extreme can affect *fund* performance at the annual horizon.

The paper that is most closely related to this one is Lou (2012). That paper, too, shows that flows affect fund performance by affecting stock prices. Trades caused by flow push prices in the direction of the flow, and subsequently these prices revert. For the results in Lou to explain my findings, it must be that stock price movements due to flow reverse within a year. However, Lou only finds reversal in the stock price movements induced by flows at long horizons: 5-12 quarters after the quarter in which the flows occurred[7]. The outflows accompanying low raw returns may be less sophisticated than other outflows, and price movements caused by such outflows should revert more strongly and more quickly. Consistent with this, I show that the sales made by funds with outflow and low raw return strongly predict performance over the next year, but the sales by funds with outflow and *high* raw return do not. This suggests that the former outflow is somehow different from the latter. One straightforward way this could happen is if it were less informed.

[7]Consequently, Lou's results do not have bearing on performance persistence at the annual horizon.

3 Data

Fund data is from CRSP. This includes fund names, net returns, expenses, styles, turnover, and asset composition.

Stock data is also from CRSP, and includes stock prices, returns, the exchanges on which the stocks are traded, and shares outstanding. The Fama-French and Carhart factors are obtained from WRDS.

At each month-end, from all fund shareclasses available on CRSP, I keep those for which there are 24 months of uninterrupted past returns data (including the current month)[8]. From these, I retain only those which reported a TNA of $5 million or greater[9] at the end of the current month. From the remaining shareclasses, I keep only those whose style at the end of the current month was among those listed in Appendix A. I then search fund names for keywords[10] indicating that the funds are index funds, and eliminate them. From the remaining, I keep only those whose last nonmissing composition report on CRSP indicated that more than 75% of their assets were in common stock and that more than 90% of their assets were in common stock and cash equivalents.

Fund holdings data is from Thomson Reuters' S12 data set. I eliminate international, municipal bond, bond and preferred, and metals funds from the S12 data set, and then construct a match between CRSP share class identifiers and S12 fund identifiers using fund names and tickers. Where more than one CRSP share class matches to the same S12 fund on one date, I retain the largest such share class (results are unaffected if instead I aggregate these shareclasses).

I take family membership and fund size from the S12 fund characteristics data set. Where fund size is missing, I use the total value of stocks held, and inflate it by the percentage of assets in common stock as reported by CRSP.

I present sample sizes in Panel A of Table 1. I count the number of funds in my sample in each month, and then take the average by year.

The sample covers 1980-2009. In tables and graphs that require monthly flow data, the sample starts in 1991, since monthly TNA data is only available from that year[11].

[8]Requiring a long history mitigates the incubation effects documented in Evans (2010). Since that paper advocates requiring 3 years of fund history, I rerun the analysis requiring 36 months of uninterrupted past return data, and get similar results.

[9]Results are robust to requiring $15 million.

[10]Specifically, I search for the following keywords: INDX, IDX, INDEX, DOW, MKT, MARKET, COMPOSITE, RUSSELL, NASDAQ, DJ, WILSHIRE, NYSE, ISHARES, SPDR, HOLDRS, ETF, STREETTRACKS, S&P 500, 100, 400, 500, 600, 1000, 1500, 2000, 3000, 5000.

[11]My basic result (examining how future alpha reacts to past alpha and past raw return) needs only fund performance data which is available from 1961 onwards. I check that my tests go through with this longer sample. Because my complete results (without testing for robustness with monthly flow measures) need fund performance and fund holdings, and the latter are available from 1980, I use this as my base case, restricting the sample to 1991-2009 where

4 Base result: flow drives down future performance

I want to study whether a fund's raw return in one year is related to its alpha in the subsequent year. A control that is obviously needed is the alpha in the current year. At the end of each month t, I estimate this 12-month alpha using the previous 24 months of data as α_t^i in the following regression:

$$R^i_{t-j+1} = \alpha^i_t + \chi^i_{t,j>12} + \beta^{i\intercal}_t f_{t-j+1} + \epsilon^i_{t-j+1} \tag{1}$$

where j goes from 1 to 24, R^i_s is the return on fund i in month s, f_s is a 4×1 vector of realizations of the four Carhart[12] factors at s, and $\chi^i_{s,j>12}$ is an indicator that takes the value of 1 for $j > 12$. The time subscripts on the coefficients indicate that their values depend on the date on which this regression is run. This regression estimates the alpha – the average idiosyncratic return – over the past twelve months, with factor loadings estimated over the past 24 months.

The percentage flow into a fund is given by

$$h^i_t = \frac{TNA_t - TNA_{t-1} * (1 + R_t)}{TNA_{t-1} * (1 + R_t)}$$

This measure of percentage flow assumes that all flow occurs at the end of the period. I get virtually identical results assuming flows occur at the beginning of the period. I adjust a fund's lagged TNA in this calculation when other funds merge into it.

4.1 Results from portfolios

I want to form portfolios by sorting funds on past four-factor alpha and past raw return. Because the two are highly correlated[13], I orthogonalize raw return before forming portfolios[14]. At each month-end, I regress funds' raw return over the past 12 months on their alpha over the past 12 months, and take the residual. I sort funds into quintiles on their alpha, and, within alpha quintiles, on the residual.

I need fund flow data. I also check that my results go through with only the 1991-2009 sample period.

[12] I also examine other factor models to construct alphas on which to sort. CAPM alphas have an average cross-sectional correlation of 0.88 with raw return, so the double sort does not produce much independent variation. The corresponding correlations are 0.70 for 3-factor alphas and 0.65 for 4-factor alphas. When I use 3-factor alphas to sort, I find that raw return is negatively related to future performance, but lacks statistical significance. This is consistent with 3-factor alphas being a noisier signal of skill than 4-factor alphas.

[13] Given that my two independent variables are highly correlated, multicollinearity might be a concern. The principal adverse effect of multicollinearity is instability in the coefficient estimates. I find that my coefficients are stable across various subsamples, subperiods and regression methods, suggesting that multicollinearity is not a serious problem.

[14] I get similar portfolio results if I sort into quintiles first by alpha and then by (unorthogonalized) raw return. In the regressions, which return variable I use to sort makes no difference to the results.

In Panel B of Table 1, I present average values of the sorting variables. The orthogonalizing procedure causes there to be little variation in alphas across raw return quintiles. In unreported results, I find the more extreme alpha and raw return buckets – the edges of the table – consist of smaller funds on average, as might be expected. Expense ratios do not show a clear pattern.

I construct 25 portfolio return series as follows. Consider the funds placed in the high-alpha high-raw return bucket in the ranking at the end of December 2000. Call the equal-weighted portfolio of these funds the *ranked portfolio* for December 2000. The portfolio I actually hold over January 2001 is the equal-weighted average of the ranked portfolios for January 2000 to December 2000. Doing this for each month for every bucket yields a single time-series of portfolio returns for each bucket. This approach is identical to that taken by Jegadeesh and Titman (1993) for stocks.

In Figure 1, I plot the flows into the fund portfolios. I do this only for the 16 portfolios[15] at the edges of the table, for the subset of data in which monthly TNA information is available (1991-2009). For my conclusions, it is essential that there is variation in flow across portfolios sorted by raw return, controlling for alpha. The top left graph shows how flow varies in the five raw return quintiles within the highest alpha quintile. The variation is substantial. High raw return funds have flows that are about 2% per month over the ranking year, while low-raw-return funds have virtually no flow (even though they have similar alphas). Among the funds in the low past alpha quintile (the graph on the top right), I find similar variation: low raw return funds have flows of about -1% per month over the ranking year, while high raw return funds have zero flows[16].

To show that flows are related to raw return in a regression, I regress flow on fund raw return and controls in Table 2. I run these regressions at the fund level, but I get similar coefficients when I run them at the portfolio level. At the end of each month, I run cross-sectional regressions, and report Fama-MacBeth coefficients and Newey West t-statistics. From the graphs, it is evident that raw return in this year affects flow both in the next year as well as in this year (i.e., contemporaneously). I examine both these effects.

In column 1 of Table 2, the dependent variable is average percentage flow per month over the next 12 months (i.e., months +1 to +12). The independent variables include fund alpha over the past year and fund raw return over the past year. Controls include fund expense ratio, the log of fund age, and lagged log fund and family size. Fund raw return is strongly related to future flow, even controlling for fund alpha.

In column 2 of the same table, I show that raw return is also related to contemporaneous flow.

[15] There are 20 curves drawn, but there are overlaps: for example, the high-raw return high-alpha funds appear both in the high-alpha graph and the high-raw return graph.

[16] I observe that there is similar variation across alpha quintiles (the two bottom graphs). My point in these graphs and associated regressions is that raw return affects fund flow, even controlling for fund alpha. That fund alpha is related to fund flow is not surprising. It does not seem likely that this will affect the predictive power of raw return.

I run average monthly flow over this year (months -11 to 0) on raw return this year (months -11 to 0) and controls. I find a strong positive relationship. This can be interpreted as a partial correlation. I use the same controls as in column 1. For lagged flow, I use flow over the months -23 to -12. To avoid the mechanical relationship between size at month 0 and flows from month -11 to 0, I use size at month -12 as a control.

Returning to the 25 Jegadeesh and Titman (1993) portfolios, given the single time series of returns for each bucket, I calculate the average raw return. Panel A of Table 3 presents mean returns in the year after ranking year. Mean returns increase across past alpha quintiles, but show little pattern across raw return quintiles[17]. Panel B presents the Carhart alphas. The point estimates decrease as the raw return increases, virtually monotonically in all alpha quintiles. Among high alpha funds, funds with low raw return continue to do well. They have a Carhart alpha of 21.7 bp/month over the next year (2.6% annually), while funds with high raw return have insignificantly negative future alphas. The difference between high and low raw return funds is negative and significant. Among funds with low past alphas, funds with high raw return continue to have negative and significant future alphas, while funds with low raw return have insignificantly negative future alphas.

The finding that alpha only persists among high alpha, low raw return funds and low alpha, high raw return funds is consistent with the intuition in Berk and Green (2004). Consider funds with high past alpha. All these funds have positive flows, but funds with high raw return have large positive flows, while funds with low raw return have small positive flows. If flow drives down future performance, then it is to be expected that the low raw return funds continue to do well, while the high raw return funds do not. Alternatively, consider funds with low past alpha. All these funds have negative flows, but funds with high raw return have small negative flows, while funds with low raw return have large negative flows. If flow is inversely related to future performance, then high raw return funds should continue to do badly, while low raw return funds should not. As a consequence, performance persistence is observed among high alpha, low raw return funds and low alpha, high raw return funds. The difference in the future alpha of these two buckets is 4.71% annually, and highly significant. In contrast, among high alpha, *high* raw return funds and low alpha, *low* raw return funds, there is no observed persistence: the difference is insignificantly *negative*.

Finally, I ensure these results are not driven by timing factor risk premia. This is a concern because the portfolios of funds with low raw return consist of high beta funds when the market

[17]Differences between the results for raw return and for Carhart alphas are likely due to the momentum effect. When I use 3-factor alphas to evaluate portfolio performance, I find that the future alphas very weakly increase in past raw return, again likely due to the momentum effect.

return has been low – that is, in bad times – and of low beta funds when the market return has been high – that is, in good times (Grundy and Martin, 2001). Since the market risk premium is high in bad times and low in good, the low-raw return portfolios are effectively going long high-beta funds when the risk premium is high and low-beta funds when the risk premium is low (and conversely for the high-raw return portfolios). In this scenario, an unconditional factor model might well report positive alphas for the low-raw return portfolios, and negative alphas for the high-raw return portfolios.

I consider a conditional model (Ferson and Schadt, 1996). I augment the Carhart model with interaction terms between the excess return on the market and demeaned lagged values of instruments known to predict the risk premium: the dividend yield of the NYSE, the lagged T-bill yield, the term spread, the default spread, and an indicator for January, and similarly for the momentum factor. The model I run is:

$$R_t = \alpha + \beta_m mktrf_t + \beta_s smb_t + \beta_h hml_t + \beta_u umd_t + \sum_{j=1}^{5} \beta_{mj} mktrf_t Z_{t-1}^j + \sum_{j=1}^{5} \beta_{uj} umd_t Z_{t-1}^j + \epsilon_t$$

where R_t is the return on the fund portfolio in month t, $mktrf, smb, hml, umd$ are the Fama-French-Carhart factors, the Z^j are the five instruments, demeaned, and ϵ_t is the regression residual.

Results for this specification are reported in Panel C of Table 3. The same pattern is observed, with results being stronger than with the unconditional model (Panel B).

In unreported tests, I allow (i) only the market beta, (ii) the market and SMB betas (iii) the market and the HML betas (iv) all factor loadings to vary, with results that are similar in magnitude and significance.

[Table 3 about here]

4.2 Results from cross-sectional regressions

I now use cross-sectional regressions to show that future performance decreases with raw return, controlling for alpha. The portfolio approach above is non-parametric and accounts naturally for survival issues. However, regressions let me control for additional variables affecting fund performance.

A problem in running cross-sectional regressions is that it is hard to measure fund alphas using monthly data. The standard way to measure alphas in a month is to estimate a factor model using, say, 36 months of data prior to the month in which the alpha is needed, and then to plug in the factor realizations in that month to calculate the expected return given the factor realizations. The issue in this situation is that the factor loadings of the fund portfolios change over the ranking and holding years.

Consider the funds with high past alpha and high past raw return. These funds are holding stocks which have done well. Consequently, in the first month after ranking (month one), the loadings of these funds on the UMD portfolio, β_{UMD}, is very high. In month two, the UMD portfolio changes, even if the portfolio of stocks the funds hold stays more or less the same. So as time passes, the funds' β_{UMD} should change towards the β_{UMD} of all funds – that is, it should drop over the year after ranking. Similarly, the β_{UMD} of these funds should increase over the ranking year. This pattern should be decreasingly apparent among funds with lower raw return, and should to be inverted for funds with the lowest raw return.

I plot β_{UMD} for the 16 fund portfolios[18] on the edges of the table in Figure 2, for each month in the 12 months before and 24 months after the ranking date. For each bucket, for each month in event time, these betas are estimated from a single time series of returns. For instance, the beta for month -10, the tenth month before the ranking date, is estimated by first constructing a single time series of the average return for funds which *will be* put into that bucket in ten months.

Consider the funds with high past alpha (top left). The betas of funds with high past raw return have the pattern described – rising over the ranking year and then falling. The betas of the funds with low past raw return show the inverted pattern. A similar pattern is seen among funds with low past alpha (top right). In contrast, controlling for raw return, there is no variation across alpha quintiles (the bottom two graphs).

For my purposes, how this problem arises is less important than its result: for each portfolio, betas vary in the months around the ranking date. Therefore, I cannot use short-horizon fund-level regressions to estimate them. A second point to be considered is that the level of the UMD betas (and their variation) is related to past raw returns.

I address these problem by estimating factor loadings in a way that takes their variation around the ranking date into account (and allows for different UMD betas for funds with different past raw return). There is a standard technique in the literature, used, for instance, by Chen et al. (2004). They test whether fund size at one date affects performance in the following month. They sort funds into quintiles by size, and create a single time series of equally-weighted portfolio returns for each quintile. They estimate factor loadings for these five time series. They calculate a fund's alpha in a given month by assuming that its loadings are the loadings of the size quintile it was in during that month.

I need to study performance over the next year, not the next month. This causes two problems.

[18]There are 20 curves drawn, but there are overlaps: for example, the high-raw return high-alpha funds appear both in the high-alpha graph and the high-raw return graph.

First, there are survivorship issues – about 4% of my sample drops out within 12 months after ranking. Second, because the loadings in each of the 12 months after ranking are different, I will have to use this technique separately for each of these months.

Accordingly, I sort funds into quintiles by fund alpha and fund raw return. For each bucket, I create a single time series of equally-weighted portfolio returns for funds that were placed in that bucket 1, 2, ... , 12 months ago. (The 1-month-ago time-series corresponds exactly to Chen et al.) This gives me 12 portfolio time-series. I run the factor model on each, giving me 12 sets of loadings. I use the loadings estimated from the 1-month ahead portfolio return series to calculate abnormal returns in the first month after ranking. I repeat for each of months 2 through 12. I do the same thing for every other bucket.

I then run Fama-Macbeth regressions. To avoid survivorship issues, I run these at the portfolio level, not the fund level. At each month-end, I run a cross-sectional regression with 25 observations, corresponding to the 25 buckets. As independent variables, I use the within-portfolio averages (winsorizing the top and bottom observations) of the following characteristics: past twelve months' alpha, past twelve months' raw return, expense ratio, log of fund size, log of family size, turnover, and log of fund age. For each bucket, the dependent variable is the average monthly portfolio alpha over the next year, constructed from the abnormal returns estimated as described above.

Results are in the first column of Table 4. As expected, future alphas increase in past alpha and decrease in past raw return. The coefficient on raw return is -0.0102, meaning that one percent in annual raw return reduces future alpha by about 1 bp/month over the next year. To get an idea of the magnitude of the effect, I standardize the right-hand side variables to have a standard deviation of 1 at each date. The coefficient on raw return is -0.00099, meaning that an increase of one standard deviation of raw return in this year decreases alpha by about 10 basis points per month in the subsequent year. Consistent with Chen et al. (2004), I find that log size reduces fund performance, and log family size increases fund performance (though the coefficient is at the margin of significance)[19].

As an alternative to the portfolio-regression approach, I retain only funds that have 12 months of return data in the year after ranking, and run the regression at the fund level. All the main results of the paper go through with this modification.

The portfolio results (in the previous subsection) suggest that the effect I am examining is stronger among the funds with higher past alphas. To check this, I include an interaction term of raw return with a dummy for being in the top two alpha quintiles. The regression coefficient

[19] I observe that an insignificant coefficient only means that family size does not explain fund performance across my alpha- and raw return-sorted portfolios. It does not mean that family size is not related to future performance in my sample.

(t-statistic) on raw return is -0.008 (1.91) and the coefficient on the interaction term is -0.0058 (2.53). I examine this phenomenon more closely in section 5.3.

[Table 4 about here]

4.3 Discussion

The previous subsections show that, controlling for alpha, raw return is negatively related to fund alpha over the next year. I argue that this is because raw return proxies for flows which are unrelated to skill.

The first question that arises is whether fund alpha is a good measure of skill, or a good measure on which to evaluate performance. Alpha is the most widely-used measure in the literature, but it may leave out components of skill or performance that investors value. However, it seems indisputable that alpha measures *some* dimension of skill/performance. In a narrow sense, the conclusions of my paper can be read as saying that raw return affects *this* dimension of performance.

A second important question is whether raw return is a good proxy for unsophisticated flows. It is possible that some aspect of skill is not captured by alpha and so gets folded into raw return. In this case, raw return may also proxy for this aspect of skill. But for this to make a difference to my results, such skill (1) must not be captured by alpha in this year, but must affect alpha in the next year and (2) must affect future alpha negatively[20]. On the face of it, it is hard to come up with such a skill.

For example, factor-timing ability is more likely to be captured by raw return than by alpha. But it is difficult to make an argument for why factor-timing ability should affect future alpha at all, controlling for current alpha[21]. One possible channel is the argument of Kacperczyk et al. (2014), who find that funds that show factor-timing ability in recessions also show stock-picking ability in booms. But the implied relationship between current raw return and future alpha is positive, not negative.

It may be that raw return proxies for other variables which have a negative relationship with future alpha. An example is fund variance, and I examine this in the next subsection. There may exist other variables which I have not controlled for. But this concern is mitigated by the fact that, later in the paper, I demonstrate a specific channel through which raw return affects future

[20]If it affected future alpha positively, then this would mean that the true relationship between raw return and future alpha is even more negative than I find.

[21]Del Guercio and Reuter (2014) find that some funds have incentives to produce alpha, others have incentives to produce raw return. Such incentives may well create an *unconditional* negative correlation between factor-timing ability and stockpicking ability. However, this will not lead to a negative relationship between future alpha and current raw return, *controlling for current alpha.*

fund performance – the stocks sold by funds with low raw returns subsequently outperform. It is difficult to believe that another unknown variable, not to do with flows, is causing both (a) raw return to have a negative relationship with alpha and (b) low-raw-return funds to sell stocks.

4.4 Robustness

4.4.1 Using the DGTW(1997) methodology to evaluate performance

I use the four-factor model of Carhart (1997), combined with the Jegadeesh and Titman (1993) approach, to measure expected returns and hence abnormal performance. An alternative is to use the approach of Daniel et al. (1997), who sort stocks into portfolios based on characteristics known to predict returns, and, in any month, use the average return of the portfolio to which the stock belongs as the expected return on that stock in that month. They then compute the expected return on a fund's portfolio as the dollar-weighted average of the expected returns of the individual stocks. This method avoids having to calculate factor loadings in order to calculate expected returns.

This method is predicated on the idea that by controlling for stock characteristics, we can control for factor exposures. In my sample, I find that even after applying the DGTW method to control for the standard stock characteristics of size, book-to-market, and prior return, funds with high raw returns have larger UMD betas than funds with low raw returns. This suggests that the DGTW method is not adequately controlling for UMD exposure. I show this in Appendix B.1.

4.4.2 Using realized flow

Instead of using raw return as a proxy for unsophisticated flow, I could examine the effect of flow itself. At the end of each month, I find the mean percentage flow in the past 12 months, keeping only funds with at least 9 flow observations. I then estimate the impact of realized flow on future alphas in a regression framework in column 2 of Table 4. I repeat the procedure used for the regression with raw return (see section 4.2), except that I form portfolios by sorting on past alpha and past realized flow (instead of raw return). I find the coefficient on flow is insignificant. This agrees well with the idea that funds have high flow because they have high skill, and this selection effect masks any negative effect of flow itself.

I then examine the effect of both realized flow and unsophisticated flow (as proxied for by raw return) in a single regression. If (a) my story is correct and if (b) raw return accounts for most of the unsophisticated flow, the coefficient on realized flow may become positive, reflecting the positive selection effect. It is more likely that raw return will not pick up all the unsophisticated flow and the coefficient on realized flow will remain insignificantly negative.

At each date, I sort funds sequentially into quartiles by each past alpha, past raw return and past realized flow. This gives me 64 portfolios at each date[22]. I then estimate the future alphas of these portfolios as in section 4.2, and regress these future alphas on past flow measures and controls. I present results from this regression in column 3 of Table 4. Raw return is negative and significant while realized flow is negative and insignificant.

4.4.3 Reversal effects in stock prices

My result is funds with low past raw return do better in the future than funds with high past raw return. This might be driven by reversal in the underlying stocks, and have nothing to do with flows at all.

Jegadeesh (1990) demonstrates that in the one month after ranking stocks on one-month performance, winner stocks do badly and loser stocks do well. Grinblatt and Moskowitz (2004) show that loser stocks do well in the January after ranking. They also demonstrate a host of momentum-related return effects in Januaries.

I leave a month between the end of the ranking period and the beginning of the holding period, and I exclude Januaries from the holding period. My results as strong as before. I also use this alpha as a dependent variable in the regressions, and find consistent results. As an alternative, I include the short-term reversal factor (STREV) in the factor models, and I find no difference in the results.

However, there might be a hitherto-unknown mechanism whereby stocks with high raw returns have low alphas next period, and vice versa. To show this is not driving my results, I can include as an additional control the raw return, over the past 12 months, of the stock portfolio the fund held on the ranking date[23]. I sort funds into quintiles at each month-end, first by their past alpha and then by the past 12 months' raw return of the stock portfolios they currently hold, and run regressions as in section 4.2. I report this regression in column 4 of Table 4. I find the stock return is insignificantly negative. This sign may be due to the fact that it is correlated with fund raw return. In column 5, I include both variables. As I did with realized flow, I sort funds into quartiles sequentially by fund alpha, fund raw return and stock raw return on the fund's current portfolio, giving me 64 portfolios at each date. In Fama-MacBeth regressions with these portfolios, I find that fund raw return is strongly negative, while stock raw return is insignificantly positive.

[22]I intend these sorts to create portfolios across which the independent variables vary. Results are robust to changing the order of sorting the flow variables and to changing the number of portfolios. If I use the 64 portfolios to regress future alphas on only past realized flow and controls and, separately, on past raw return and controls, raw return continues significant, while realized flow is insignificant.

[23]This stock portfolio's past 12 month return will differ from the fund's past 12 month return to the extent that the fund has turned its portfolio over in that period.

4.4.4 Variance effects

My result is that funds with high raw returns do badly, and those with low raw returns do well. Because funds with raw returns that are large in magnitude may, on average, be funds with large factor exposures, I might be picking up an effect where high-variance (either systematic or total variance) funds do worse. I control for each kind of variance in the regression, in the same way as I do for flow (section 4.4.2), and find that my results are unaffected. I also include Huang et al. (2011)'s measure of risk-shifting as an additional control, with little change to my results.

4.4.5 We may not expect persistence in the alphas of funds where performance does not, in fact, persist

There are two reasons why we may not expect persistence in the alphas of high-alpha funds with high raw return and of low-alpha funds with low raw return. The first is that these funds are of a kind where we would not, ex ante, expect persistence. Cremers and Petajisto (2009) and Da et al. (2011) argue that performance should be persistent among specific subsets of funds – Cremers and Petajisto (2009) consider funds with a high "active share" and Da et al. (2011) funds which trade in high-PIN stocks[24]. If the high-raw return, high-alpha funds and low-raw return, low-alpha funds are outside these subsets, it would not be strange to find that their alphas do not persist. To test this, I calculate the mean active share and the mean trade-weighted PIN for funds in each of my buckets. I find no discernible pattern in the difference in active share and trade-weighted PIN between high and low raw return funds.

A second reason we may not expect persistence among these funds is if, within alpha quintiles, measurement error in the past alpha is correlated with past raw return. In this case, the past alphas of the funds with high raw return are overestimated and the past alphas of those with low raw return are underestimated. Thus, for example, among high-alpha funds, the funds with high raw return will do worse than those with low raw return simply because they were less skilled to begin with.

A way to address general measurement error concerns is to use the "back-testing" technique of Mamaysky et al. (2007). To do this, before I perform the double sort at each date, I eliminate funds in which the measured alpha and the raw return have different signs. Imposing this filter does not change my results.

A specific way that measurement error might arise in my context is because the UMD betas of the portfolios vary over the ranking year (see Figure 2 and section 4.2). I examine this concern in

[24]Data for active share was obtained from Antti Petajisto's website, and PIN data was obtained from Lance Young. Similar results are obtained using the adjusted PIN of Duarte and Young (2009).

Appendix B.2, and find it is unlikely to be driving the results.

5 Using holdings data

The results in the previous section show that future fund alphas decrease with raw return. These results are consistent with the mechanism employed in Berk and Green (2004)'s model: flows causing increases in size and consequent diseconomies of scale. However, any mechanism through which flow is negatively related to future performance – not necessarily changing costs via changing size – will deliver similar results. In this section, I use holdings data to examine the channel through which fund performance is affected. I find that trades by funds with low raw return affect stock prices, and therefore affect fund performance.

5.1 Construction of measures of aggregate buys and sales by funds affected by unsophisticated flow

A straightforward way in which flow might affect future fund performance is if it affected stock prices. How might this happen? Prior research (Lou, 2012) has found that funds respond to flow by scaling their positions up or down. These trades are unlikely to contain information[25], but may, in aggregate, move stock prices. Therefore, stocks in which positive-flow funds have increased their positions will likely have gone up in price on no information, and so would be expected to underperform. Because flows chase performance, these stocks are likely to be the ones held by well-performing funds, and the reversal will result in these funds underperforming. Conversely, stocks sold by funds with outflows should outperform, causing improvement in the performance of funds that have done badly this period.

This argument is intuitive and plausible. But Lou (2012) finds no evidence for reversal in price movements due to flow in the year following the flow. Instead, he finds evidence for continuation from one quarter to the next, and reversal at horizons longer than a year. However, price movements due to *unsophisticated* flows may well reverse more quickly than movements due to flows in general. In what follows, I construct aggregate trade measures based on my proxy for unsophisticated flow – raw return – and test how these affect future fund performance.

My goal, then, is to estimate, for each stock, how much it has been (a) bought up by funds with high unsophisticated flow and (b) sold by funds with low unsophisticated flow. At each date, I regress fund raw return on fund alpha in cross-section. I use the the residual from this regression as a measure of unsophisticated flow.

[25] Alexander et al. (2007) show that flow-motivated trades contain less information than trades not motivated by flow.

For each stock, I construct a measure of the aggregate ranking-year buys that were induced by unsophisticated flow. I calculate this as the sum of the increases in existing positions by positive unsophisticated-flow funds. I weight the sums by the absolute value of the return residual, so that buys by funds with larger flows are weighted more heavily. Results are robust to not weighting. I deflate the measure by the stock's shares outstanding. I construct a measure of the aggregate ranking-year unsophisticated-flow-induced sales analogously, by summing the decreases in positions of funds with negative unsophisticated flow. The aggregate sales variable is the (weighted) sum of negative changes in holdings, and so can take only nonpositive values. Analogously, the aggregate buys variable can take only nonnegative values.

I intend these measures to proxy for the informationless change in stock price due to trades caused by unsophisticated flows. To this end, first, I leave out three kinds of trades: sales by funds with high raw returns, buys by funds with low raw returns, and initiations of new positions by funds with high raw returns. These trades are more likely to be information-driven than the ones included. Second, I use the return residual, rather than the return itself, to define positive and negative unsophisticated-flow funds. Using the raw return itself would mean, for instance, that trades by funds with high alphas (and high returns) are treated in the same way as those by funds with low alphas (and similar high returns). The buys by the latter set of funds, for example, are less likely to contain information than the buys by the former.

There are about twice as many trades driven by negative unsophisticated flow as there are ones driven by positive unsophisticated flow. The magnitude of the negative flow-driven trading, among stocks affected by such trading, is also about twice the magnitude of positive flow-driven trading among stocks affected by positive flow-driven trading. This suggests that funds experiencing positive flow diversify more rapidly at the annual horizon than at the quarterly, where they respond to inflow largely by scaling up existing holdings (Lou, 2012). This provides a reason why I find that aggregate buys are less important than sales in predicting fund performance.

I construct fund-level measures by taking the holding-weighted averages of the stock-level measures across the stocks the fund held on the ranking date. If a fund ranks high on the buys measure, then its ranking-date stock portfolio contains stocks which have been bought up by funds with high raw return, moved up in price, and which may be expected to underperform. Conversely, if a fund ranks low on the sales measure, its ranking-date stock portfolio contains stocks which have been sold by funds with low raw return, moved down in price, and which may be expected to outperform.

The fund-level measures are positively correlated with each other, the average cross-sectional correlation being 0.28. Both measures are, by construction, highly correlated with fund raw return. The average cross-sectional correlation is 0.46 for aggregate buys and 0.37 for aggregate sales. Both measures are virtually uncorrelated with fund alpha: the average cross-sectional correlation is 0.07

for buys and -0.02 for sales.

5.2 Aggregate unsophisticated-flow-driven trades of a fund's portfolio predict fund performance

I start by running regressions to predict future fund alpha, using the fund-level aggregate trade variables as predictors. I run these at the portfolio level, to avoid survivorship bias and the effect of changing momentum betas (see section 4.2). I sort funds into terciles sequentially by past fund alpha, past fund raw return (orthogonalized relative to alpha), aggregate unsophisticated-flow induced sales and aggregate unsophisticated-flow induced buys. Results are robust to changing the order of the aggregate trade variables. This gives 81 portfolios at each date, which I use to run Fama-MacBeth regressions. Results are in the first five columns of Table 5. I first confirm that using a different set of portfolios with which to run regressions does not affect my base result. In column 1 I show that when I run future fund alpha on past fund alpha and past fund raw return, alpha enters positively and raw return negatively. The estimates closely resemble the earlier results (column 1 of Table 4) in magnitude and significance.

I then use aggregate unsophisticated-flow induced sales and buys as predictors, first separately in columns 2 and 3, and then together in column 5. The coefficient on sales is negative and strongly significant, while that on buys is insignificant. The sales measure subsumes the predictive power of raw return, suggesting that raw return, when used alone, is picking up movements in the stock prices from unsophisticated-flow-driven sales.

The fact that buys are insignificant is not surprising. Funds which suffer outflows are likely to be holding correlated positions. To meet the outflows, they are compelled to sell the stocks they hold, resulting in concentrated price pressure. Funds with inflows are also likely to be holding correlated positions (since flow chases performance), but the difference is that they are not compelled to invest them in their current positions. They can invest the inflows in any stocks, and so the price pressure is likely to be dissipated.

In column 4 of Table 5, I use the aggregate unsophisticated-flow induced *net* buys as a predictor. To calculate this, for each stock, I sum the aggregate unsophisticated-flow induced buys and the aggregate unsophisticated-flow induced sales, and then calculate the fund-level measure as before. This fund-level variable is essentially the sum of fund-level aggregate buys and fund-level aggregate sales. It has strong predictive power, but from the other regressions it is clear that this power comes entirely from the aggregate sales.

I then confirm that these measures affect the future performance of the stocks the funds held on the ranking date. In column 7 of Table 5, I run a regression where the dependent variable is the alpha, measured over the year after ranking, of the stock portfolio the fund held on the ranking date (rather than the alpha of the fund itself). As expected, I find that the alpha decreases with the aggregate unsophisticated-flow induced sales, and the effect of buys is insignificant. The coefficient on aggregate sales is -0.0033, identical to its effect on future *fund* performance in column 5.

I then show directly that the aggregate trade variables affect future fund performance principally through their effect on the ranking-date stock portfolio. In column 6, I repeat the regression from column 5, but include as an additional control the future alpha of the ranking-date stock portfolio. This is the alpha, over the year after ranking, of the stock portfolio that the fund was known to hold on the ranking date (and so is contemporaneous with the dependent variable). The argument is this: suppose the effect of aggregate unsophisticated-flow induced sales on future fund performance is through the the prices of the stocks held on the ranking date. Then, if I include the future alpha of this stock portfolio on the right hand side, it should be significant, and it should reduce the coefficient on the aggregate unsophisticated-flow induced sales. On the other hand, if funds turn their portfolios over very quickly, then the future alpha of the ranking date stock portfolio should not be related to the future alpha of the fund.

I find that the ranking date portfolio's alpha is strongly significant. Including this variable reduces the coefficient on aggregate unsophisticated-flow induced sales to virtually zero and insignificant (from -0.0033 to -0.0006, comparing column 6 with column 5), and the change itself is significant (t-statistic 2.92). This suggests that the aggregate sales variable affects the fund's future alpha primarily through its effect on the ranking-date stock portfolio.

I observe that the coefficient on raw return is significantly negative in this regression, with a value of -0.0035. The coefficient on raw return has changed little from column 5, where it was -0.0044. The t-statistic of the change is 0.41. This suggests that, after controlling for the performance of the stocks the fund holds today, raw return does appear to affect future fund performance. I caution that this regression is not predictive.

Thus, using regressions, I have shown that funds whose current portfolios have been sold, in aggregate, by funds with low raw returns, do better in the future. I now show the same result in a portfolio context. In Table 6, I show that fund performance responds to aggregate unsophisticated-flow induced trades. I form portfolios by sorting funds into quintiles by past alpha and past aggregate unsophisticated-flow induced trades. I present 4-factor alphas. The panels in this table are directly comparable to Panel B of Table 3. The results, as expected, are stronger when sorting with aggregate unsophisticated-flow induced sales (Panel A)[26] rather than buys (Panel B). In this univariate analysis, the aggregate unsophisticated-flow induced buys only shows some predictive power among the funds with the highest alphas.

I then show predictability in the performance of the stock portfolio the fund held on the rank-

[26]Observe that the sales measure is the (weighted) sum of sales: negative changes in holdings. Therefore it can take non-positive values only. As a consequence, "low aggregate sales" means "heavily sold".

ing date. In Table 7, I sort funds sequentially into quintiles by fund alpha and the aggregate unsophisticated-flow induced trades of their ranking-date stock portfolios, and I look at the future alpha of these stock portfolios. The alphas of these stock portfolios can be compared to the alpha of the funds themselves (Table 6). In Panel A, I sort by aggregate sales and in Panel B, by aggregate buys. As expected, the alpha of these stock portfolios decreases in the aggregate unsophisticated-flow induced trade variables. The difference between the alpha of the high-alpha, low-trade funds and that of the low-alpha, high-trade funds is 36.9 bp/month (t-statistic 2.50) when sorting by aggregate sales, and 26.7 bp/month (t-statistic 2.12) when sorting by aggregate buys. In general, the predictive power of buys appears to be weaker than that of sales.

The final step in the portfolio analysis is to decompose the performance of the funds in the year after ranking into two components: one coming from the portfolio the fund holds on the ranking date, and the second coming from changes made since then. This decomposition is fairly detailed, and only confirms the results from the regressions: the spread in alpha among funds sorted by aggregate sales comes virtually entirely from the spread in alpha of the portfolios they held on the ranking date. For brevity, I describe the decomposition in an appendix (Appendix B.4).

In conclusion, my results indicate that aggregate unsophisticated-flow induced sales strongly affect future fund performance: the more a fund's portfolio has been sold, the better the fund's future performance. This provides a mechanism through which flows can affect performance persistence: specifically, aggregate flow-driven sales of the stocks in a fund's portfolio improve the fund's future performance. Consequently, if a fund has done badly, this reduces performance persistence. However, if a fund has done well, this mechanism should result in an *increase* in the appearance of performance persistence.

5.3 The effect of aggregate unsophisticated-flow induced trades on high-alpha funds

In the portfolio results, I noted that the effects I examined are stronger among high-alpha funds. To confirm this, I run separate regressions for the high-alpha sample. Because these results, while interesting, are incidental to the principal effect I explore, I defer them to Appendix B.3. In short, the findings are that the aggregate trade measures appear to affect all funds the same way. Among high-alpha funds, raw return does have an effect on future performance, whether or not I control for the trade measures. This may explain why some results appear stronger for such funds.

5.4 The interaction between realized flow and raw return

In this subsection, I study the interaction between trades by funds with high and low realized flow and trades by funds with high and low raw return.

My results so far indicate that the prices of stocks sold by funds with low raw returns in one year revert over the next year, thereby improving the performance of the funds that hold them. An intuitive explanation for this result is that the sales were because of unsophisticated outflows, the price pressure was nonfundamental, and so the prices revert quickly.

The immediate implication of this explanation is that it is sales by funds with *both*, low raw return and outflow, which should matter for future fund performance. There are two facets to this:

1. Sales by funds with low raw return should matter for future performance only if those funds also had outflow ("flow matters"). If I were to find that sales by funds with low raw return predict future performance no matter what flow those funds had, it would suggest that the effect I find has to do with raw return, and not with flow.

2. Sales by funds with outflow should matter for future performance only if those funds also had low raw returns ("raw return matters"). If I were to find that sales by funds with outflows predict future performance regardless what raw return those funds had, it would suggest that the effect I find is merely an expression of already-known effects at a different horizon.

I test these hypotheses in a unified framework. I use data from 1991-2009, since monthly flow data is only available after 1991. I construct aggregate trade measures based on both raw return and flow. For each stock, I construct the aggregate trades as all combinations of buys/sales by funds with high/low raw return and high/low flow. This gives $2 \times 2 \times 2 = 8$ variables. For example, for each stock, I construct the "aggregate sales by funds with low raw return and low flow" as the sum of sales by funds with low raw return and low flows, deflated, as usual, by shares outstanding. It is not clear what I should weight the trades by in the sum – whether by flow or by raw return – so I do not weight them[27]. I then construct fund-level measures by taking averages across all stocks in a fund's portfolio. I will show that of these eight aggregate trade variables, the only one that matters for performance over the next year is the sales by funds with both low raw returns and low flows.

After constructing these fund-level variables, I sort funds into quartiles by past alpha and past raw return, and then into terciles by total aggregate sales (as the sum of the four aggregate sales measures) and total aggregate buys (likewise)[28]. This gives me $4 \times 4 \times 3 \times 3 = 144$ portfolios at each date, with which to run Fama-MacBeth regressions.

[27] My prior results do not change if I use unweighted trade measures.

[28] Because my sample increases in size over time, starting in 1991 means that I can form more portfolios than if I started in 1980. Consequently, here I can sort funds into quartiles and then terciles, rather than using terciles for all variables as in Table 5. I consider other ways of forming the portfolios, and find that the only variable that is consistently significant across all specifications is the sales by funds with both low raw return and low flow.

Results are in table 8. As a sanity check, to make sure that the difference in portfolio formation does not affect my results, in column 1 I run future fund alpha on past fund alpha and past fund raw return. The former is positive and significant and the latter negative and significant, as before.

In column 2, I show that sales by funds with both, low raw returns and low flow, predict future fund alphas, and subsume the predictive power of raw return. Buys by funds with high raw returns and high flows are insignificant.

I observe that the coefficient on sales in this column is smaller in magnitude than in the corresponding column of Table 5. Here it is -0.0003, there it was -0.0033 (column 5). The reason is that the aggregate sales measure in Table 5 is a weighted sum, with the weights being the residuals from regressing alpha on raw return in cross-section. In this table, in contrast, the sum is unweighted. If I do not use weights in Table 5, I find the coefficient on aggregate sales is -0.00016. As might be expected, the effect of sales by funds with both, low raw return and outflow (this table), is stronger than the effect of sales by funds with raw return alone (previously used).

In columns 3 and 4, I test the "flow matters" facet. To do this, I use sales by funds with low raw returns and *high* flows as a predictor, both singly – in column 3 – and in combination with sales by funds with low raw return and low flow. (I also include the corresponding buys variables, but these are never consistently significant). While the former variable is marginally significant when entered alone, it is insignificant when I include both variables.

I conclude that low raw return, by itself, is not associated with sales that have price reversion at the annual horizon. It is the sales made by funds with both low raw return and outflow that show such reversion.

In columns 5 and 6, I test the "raw return matters" facet. To do this, I use sales by funds with *high* raw returns and low flows as a predictor, both singly – in column 5 – and in combination with sales by funds with low raw return and low flow in column 6. The former variable is never significant.

A possible explanation is that all outflows are not the same. Some, like those accompanying low raw return, are especially uninformed, and so the price movements they cause revert quickly. For others, the price movements they cause are either never reversed or reverse at horizons longer than a year. The finding that the outflows which accompany low raw return are different from outflows in general helps distinguish the conclusions of my paper from other papers that talk about the effect of flow on stock prices.

In column 7, I use all trade variables on the right-hand side. I find that only the sales by funds with low raw return and low flow are significantly related to future performance. All other combinations are insignificant.

I conclude that only the sales by funds with both, low raw returns and outflows, cause price movements that revert over the next year.

6 Conclusion

I form portfolios by sorting funds on past alpha (as a proxy for skill) and past raw return (as a proxy for unsophisticated flow). The subsequent performance of these portfolios increases in alpha and decreases in raw return. As a consequence, performance appears to persist among outperforming funds with low raw returns and underperforming funds with large raw returns. On the surface, this agrees well with the intuition in Berk and Green (2004).

I then show the aggregate unsophisticated-flow induced sales of the fund's ranking-date stock portfolio predicts future fund performance, and is a better predictor of future performance than the raw return of the fund itself. This implies that one way in which flows affect future fund returns is by changing the prices of the stocks that funds hold. A fund whose portfolio has, in aggregate, been sold by funds with low raw returns does better in the future. This weakens performance persistence among poorly-performing funds, but strengthens it among outperformers. Consequently, my results deepen the mystery of the lack of persistent outperformance.

However, this stock-based mechanism is not the only way through which flows affect performance. For example, among high-alpha funds, the fund's raw return remains a significant predictor of fund performance even controlling for the future performance of the stocks the fund holds. This suggests a role for other, fund-level mechanisms. What particular mechanism is at work remains an interesting topic for future research.

References

Alexander, G. J., Cici, G., Gibson, S., 2007. Does motivation matter when assessing trade performance? An analysis of mutual funds. Review of Financial Studies 20, 125–150.

Berk, J. B., Green, R. C., 2004. Mutual fund flows and performance in rational markets. Journal of Political Economy 112, 1269–1295.

Berk, J. B., Tonks, I., 2007. Return persistence and fund flows in the worst performing mutual funds, NBER Working Paper No. W13042.

Bollen, N. P., Busse, J. A., 2005. Short-Term Persistence in Mutual Fund Performance. Review of Financial Studies 18, 569–597.

Carhart, M. M., 1997. On persistence in mutual fund performance. Journal of Finance 52, 57–82.

Chen, J., Hong, H., Huang, M., Kubik, J. D., 2004. Does fund size erode mutual fund performance? The role of liquidity and organization. American Economic Review 94, 1276–1302.

Coval, J., Stafford, E., 2007. Asset fire sales (and purchases) in equity markets. Journal of Financial Economics 86, 479–512.

Cremers, M., Petajisto, A., 2009. How active is your mutual fund manager: a new measure that predicts performance. Review of Financial Studies 22, 3329–3365.

Da, Z., Gao, P., Jagannathan, R., 2011. Informed trading, liquidity provision, and stock selection by mutual funds. Review of Financial Studies 24, 675–720.

Daniel, K., Grinblatt, M., Titman, S., Wermers, R., 1997. Measuring mutual fund performance with characteristic-based benchmarks. Journal of Finance 52, 1035–1058.

Del Guercio, D., Reuter, J., 2014. Mutual fund performance and the incentive to generate alpha. Journal of Finance 69, 16731704.

Del Guercio, D., Tkac, P. A., 2002. The determinants of the flow of funds of managed portfolios: Mutual funds versus pension funds. Journal of Financial and Quantitative Analysis 37, 523–557.

Duarte, J., Young, L., 2009. Why is PIN priced? Journal of Financial Economics 91, 119–138.

Edelen, R. M., Evans, R. B., Kadlec, G. B., 2007. Scale effects in mutual fund performance: The role of trading costs, working paper.

Elton, E., Gruber, M. J., Blake, C., 2012. Does mutual fund size matter? The relationship between size and performance. Review of Asset Pricing Studies 2, 31–55.

Evans, R. B., 2010. Mutual fund incubation. Journal of Finance 65, 1581–1611.

Ferson, W. E., Schadt, R. W., 1996. Measuring fund strategy and performance in changing economic conditions. The Journal of Finance 51, 425–461.

Frazzini, A., Lamont, O., 2008. Dumb money: Mutual fund flows and the cross-section of stock returns. Journal of Financial Economics 88, 299–322.

Glode, V., Hollifield, B., Kacperczyk, M., Kogan, S., 2012. Time-varying predictability in mutual fund returns, working paper.

Grinblatt, M., Moskowitz, T. J., 2004. Predicting stock price movements from past returns: the role of consistency and tax-loss selling. Journal of Financial Economics 71, 541–579.

Gruber, M. J., 1996. Another puzzle: The growth in actively managed mutual funds. Journal of Finance 51, 783–810.

Grundy, B. D., Martin, J. S., 2001. Understanding the nature of the risks and the source of the rewards to momentum investing. Review of Financial Studies 14, 29–78.

Huang, J., Sialm, C., Zhang, H., 2011. Risk shifting and mutual fund performance. Review of Financial Studies pp. 2575–2616.

Jegadeesh, N., 1990. Evidence of predictable behavior of security returns. Journal of Finance 45, 881–898.

Jegadeesh, N., Titman, S., 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. Journal of Finance 48, 65–91.

Kacperczyk, M., Sialm, C., Zheng, L., 2008. Unobserved actions of mutual funds. Review of Financial Studies 21, 2379–2417.

Kacperczyk, M., van Nieuwerburgh, S., Veldkamp, L., 2014. Time-varying fund manager skill. Journal of Finance 69, 1455–1484.

Lou, D., 2012. A flow-based explanation for return predictability. Review of Financial Studies pp. 3457–3489.

Lynch, A. W., Musto, D., 2003. How investors interpret past fund returns. Journal of Finance 58, 2033–2058.

Mamaysky, H., Spiegel, M., Zhang, H., 2007. Improved forecasting of mutual fund alphas and betas. Review of Finance 11, 359–400.

Pollet, J. M., Wilson, M. I., 2008. How does size affect mutual fund behaviour? Journal of Finance 63, 2941–2969.

Reuter, J., Zitzewitz, E., 2013. How much does size erode mutual fund performance? A regression discontinuity approach, NBER working paper.

Sirri, E. R., Tufano, P., 1998. Costly search and mutual funds flows. Journal of Finance 53, 1589–1622.

Wermers, R., 2004. Is money really smart? New evidence on the relation between mutual fund flows, manager behavior, and performance persistence, working paper, University of Maryland.

Yan, X., 2008. Liquidity, investment style, and the relation between fund size and fund performance. Journal of Financial and Quantitative Analysis 43, 741–767.

Zheng, L., 1999. Is money smart? A study of mutual fund investors fund selection ability. Journal of Finance 54, 901–933.

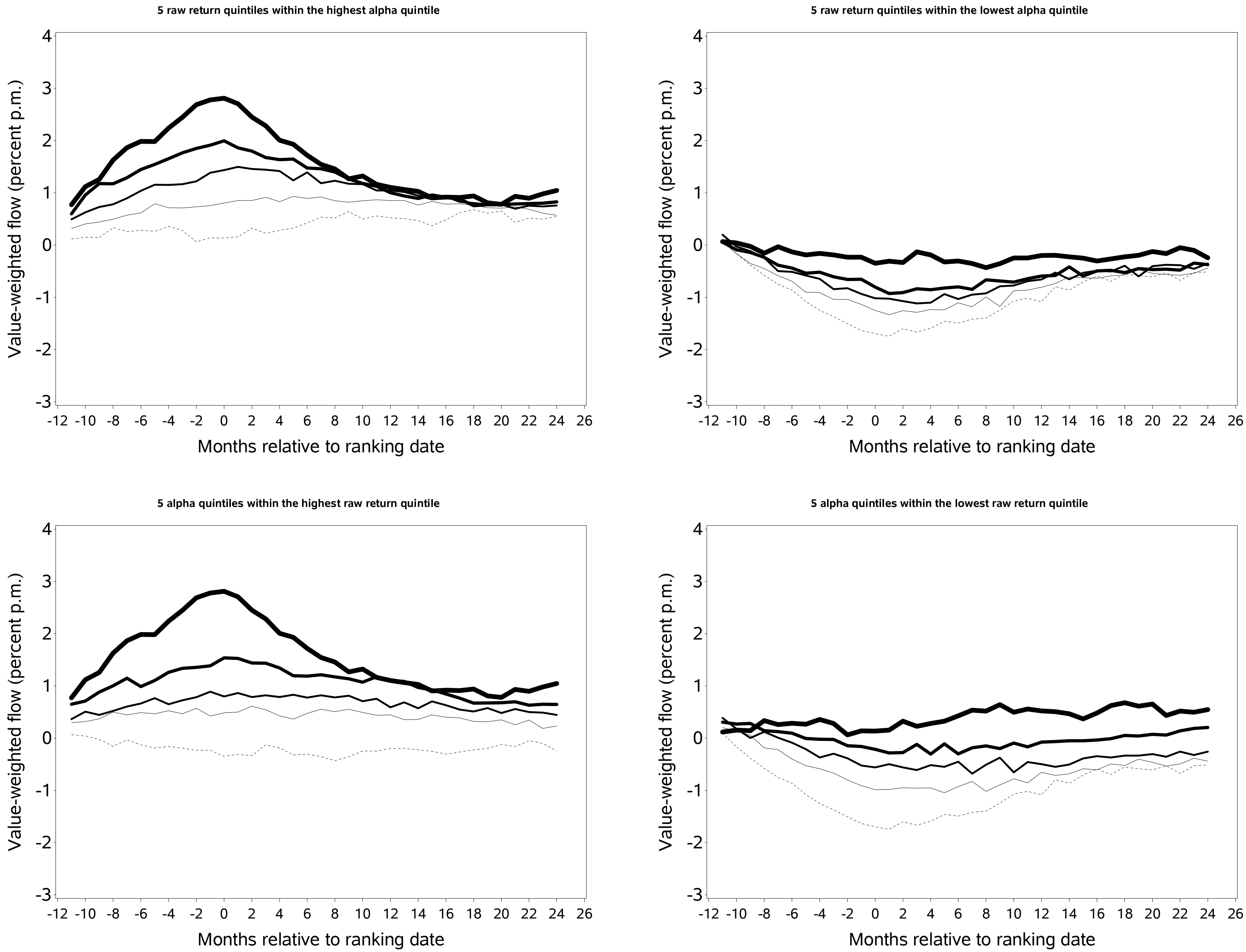

Figure 1: Flows: Event-time variation in the flows into fund portfolios. Portfolios are formed at the end of each month by sorting funds into quintiles along the past 12 months' 4-factor alpha and raw return (orthogonalized to alpha). Month 0 is the date of ranking. Only the 16 extreme portfolios are shown. In each graph, the thickest line represents the portfolio with the highest value of the sorting variable that is allowed to vary. The thinner lines represent flows into portfolios with progressively lower values of that variable. For instance, in the top left graph, the thickest line represents the flows into the portfolio with the highest raw returns (within the highest alpha quintile). Sample period is 1991-2009.

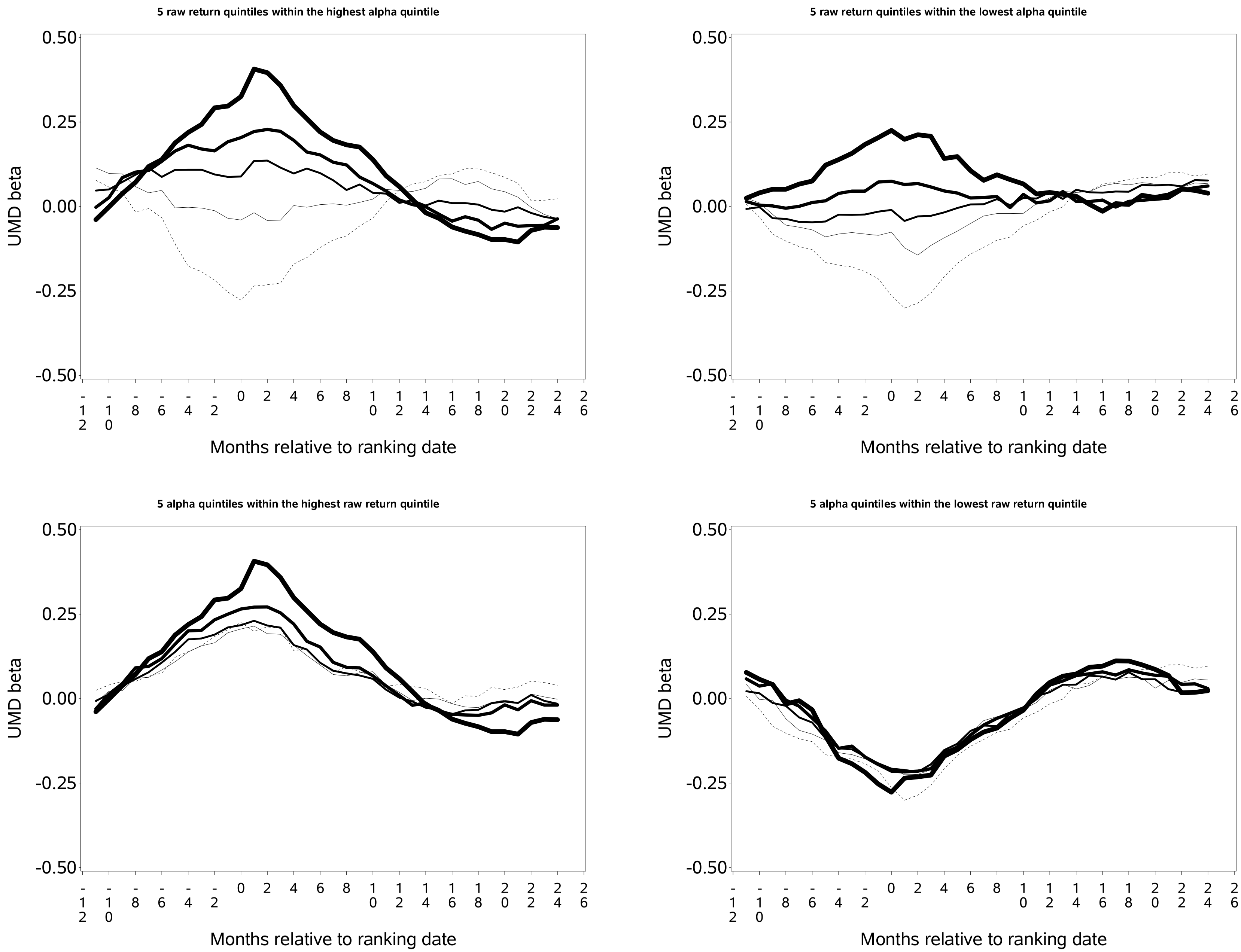

Figure 2: Betas on UMD: Event-time variation in the betas of fund portfolios on Carhart (1997)'s UMD factor. Portfolios are formed at the end of each month by sorting funds into quintiles along the past 12 months' 4-factor alpha and raw return (orthogonalized to alpha). Month 0 is the date of ranking. Only the 16 extreme portfolios are shown. In each graph, the thickest line represents the portfolio with the highest value of the sorting variable that is allowed to vary. The thinner lines represent the betas of portfolios with progressively lower values of that variable. For instance, in the top left graph, the thickest line represents the UMD beta the portfolio with the highest raw returns (within the highest alpha quintile). Sample period is 1980-2009.

Table 1: Sample sizes and past values of sorting variables: At the end of each month, I sort funds into quintiles based on their past twelve months' four-factor alpha and their past 12 months' raw return (orthogonalized to alpha). In Panel A, I count the number of funds in my sample at the end of each month, and then average the counts by year. In Panel B, I report the average four-factor alphas (monthly) and raw return (annual) over the past 12 months for the fund portfolios. Sample period is 1980-2009.

Panel A: Frequency counts

Year	Average number of funds in sample
1980	121.70
1981	127.33
1982	111.50
1983	126.08
1984	157.00
1985	153.42
1986	172.75
1987	175.42
1988	179.25
1989	188.33
1990	200.33
1991	250.92
1992	265.25
1993	399.00
1994	479.67
1995	615.58
1996	703.33
1997	832.67
1998	857.33
1999	1,043.08
2000	1,087.83
2001	1,053.92
2002	1,062.50
2003	1,415.17
2004	1,529.83
2005	1,535.58
2006	1,560.00
2007	1,529.42
2008	1,495.92
2009	1,374.92

Panel B: Past values of sorting variables

B.1: Unconditional 4-factor alphas (percent p.m.)

	Past alpha quintile						
	Low	2	3	4	High	Row Avg.	High-Low
Past raw return quintile							
Low	-0.857	-0.293	-0.026	0.251	0.930	0.001	1.787
2	-0.851	-0.293	-0.028	0.242	0.791	-0.027	1.642
3	-0.840	-0.290	-0.027	0.244	0.805	-0.021	1.644
4	-0.844	-0.290	-0.028	0.248	0.876	-0.007	1.720
High	-0.888	-0.292	-0.025	0.251	1.006	0.011	1.894
Col. Avg.	-0.856	-0.292	-0.027	0.247	0.881	-0.009	1.737
High-Low	-0.031	0.001	0.000	0.000	0.075	0.010	

B.2: Raw return (percent p.a.)

	Past alpha quintile						
	Low	2	3	4	High	Row Avg.	High-Low
Past raw return quintile							
Low	-5.500	0.061	2.726	4.947	9.123	2.273	14.623
2	-0.100	5.482	8.139	10.742	16.052	8.070	16.152
3	3.590	8.960	11.456	14.443	21.492	11.989	17.903
4	7.338	12.467	15.084	18.489	27.601	16.204	20.262
High	13.850	18.792	21.289	25.269	36.804	23.205	22.955
Col. Avg.	3.876	9.188	11.776	14.814	22.278	12.390	18.402
High-Low	19.350	18.731	18.562	20.322	27.681	20.932	

Table 2: Determinants of flow: At the end of each month, I run cross-sectional regressions of flow on lagged flow, performance variables, and controls. Fama-MacBeth estimates with t-statistics based on Newey-West standard errors are reported. In column (1), I regress flow over the year after ranking on performance variables and fund characteristics. I also include lagged flow (i.e., flow in the year before ranking) as a control. In column (2), the dependent variable is flow in the year before ranking, and the independent variables are lagged appropriately. The sample period is 1991-2009.

Dependent variable	(1) Average flow per month months +1 to +12	(2) Average flow per month months −11 to 0
Fund alpha in months −11 to 0	0.5119	0.5501
	(5.25)	(5.30)
Fund raw return in months −11 to 0	0.0463	0.0708
	(4.36)	(11.79)
Average flow in months −11 to 0	0.2217	
	(11.01)	
Average flow in months −23 to −12		0.1356
		(7.20)
Log(size) at the end of month 0	-0.0017	
	(-4.92)	
Log(family size) at the end of month 0	0.0001	
	(2.30)	
Log(size) at the end of month −12		-0.0032
		(-6.37)
Log(family size) at the end of month −12		0.0002
		(2.72)
Expense ratio at the end of month 0	-0.2752	-0.4463
	(-3.53)	(-3.80)
Log(age) at the end of month 0	-0.0029	-0.0066
	(-8.25)	(-6.10)

Table 3: Raw return affects future fund performance (portfolios): Fund raw returns and four-factor alphas (percent p.m.), net of expenses, for portfolios formed by sorting funds on their past twelve months' four-factor alpha and their past 12 months' raw return (orthogonalized to alpha) at the end of each month. Portfolios are held for 12 months after formation. White t-statistics are in parentheses. The sample period is 1980-2009.

Panel A: Raw returns							
	Past alpha quintile						
	Low	2	3	4	High	Row Avg.	High-Low
Past raw return quintile							
Low	0.863	0.946	0.967	1.068	1.170	1.003	0.307
	(3.22)	(3.78)	(3.94)	(4.28)	(4.35)	(3.93)	(4.89)
2	0.881	0.951	0.961	1.040	1.163	0.999	0.282
	(3.50)	(4.02)	(4.12)	(4.40)	(4.47)	(4.14)	(4.19)
3	0.891	0.930	0.953	1.026	1.074	0.975	0.183
	(3.59)	(4.01)	(4.12)	(4.29)	(3.97)	(4.04)	(2.23)
4	0.875	0.944	0.968	1.039	1.062	0.978	0.187
	(3.49)	(3.94)	(4.05)	(4.17)	(3.73)	(3.92)	(1.99)
High	0.925	0.949	0.966	1.048	1.050	0.988	0.125
	(3.47)	(3.69)	(3.77)	(3.86)	(3.41)	(3.67)	(1.25)
Col. avg.	0.887	0.945	0.964	1.045	1.104	0.989	0.217
	(3.50)	(3.94)	(4.06)	(4.28)	(4.06)	(4.00)	(3.05)
High-Low	0.062	0.004	-0.001	-0.020	-0.120	-0.015	
	(0.48)	(0.03)	(-0.01)	(-0.15)	(-0.69)	(-0.12)	

Panel B: Unconditional 4-factor alphas							
	Past alpha quintile						
	Low	2	3	4	High	Row Avg.	High-Low
Past raw return quintile							
Low	-0.105	-0.023	0.003	0.105	0.217	0.039	0.322
	(-1.26)	(-0.31)	(0.04)	(1.39)	(2.27)	(0.52)	(5.07)
2	-0.128	-0.051	-0.032	0.047	0.152	-0.002	0.280
	(-2.05)	(-1.08)	(-0.71)	(0.97)	(2.73)	(-0.05)	(4.29)
3	-0.152	-0.076	-0.056	0.010	0.027	-0.049	0.178
	(-2.82)	(-2.04)	(-1.69)	(0.25)	(0.50)	(-1.50)	(2.62)
4	-0.184	-0.104	-0.066	-0.008	-0.032	-0.078	0.152
	(-3.40)	(-2.85)	(-1.92)	(-0.17)	(-0.49)	(-2.10)	(2.11)
High	-0.176	-0.142	-0.117	-0.057	-0.123	-0.123	0.053
	(-2.31)	(-2.59)	(-2.09)	(-0.77)	(-1.37)	(-2.00)	(0.65)
Col. avg.	-0.149	-0.079	-0.053	0.020	0.047	-0.043	0.197
	(-2.87)	(-2.12)	(-1.60)	(0.49)	(0.92)	(-1.19)	(3.34)
High-Low	-0.072	-0.118	-0.120	-0.162	-0.340	-0.162	
	(-0.62)	(-1.15)	(-1.18)	(-1.41)	(-2.39)	(-1.49)	

Panel C: Conditional 4-factor alphas: time-varying market and momentum betas							
	Past alpha quintile						
	Low	2	3	4	High	Row Avg.	High-Low
Past raw return quintile							
Low	-0.087	-0.025	0.011	0.119	0.285	0.061	0.373
	(-1.25)	(-0.39)	(0.18)	(1.81)	(3.44)	(0.97)	(5.51)
2	-0.163	-0.073	-0.059	0.009	0.137	-0.029	0.301
	(-2.82)	(-1.71)	(-1.43)	(0.20)	(2.53)	(-0.74)	(4.35)
3	-0.187	-0.098	-0.078	-0.021	0.004	-0.076	0.192
	(-3.46)	(-2.75)	(-2.63)	(-0.57)	(0.08)	(-2.37)	(2.73)
4	-0.220	-0.140	-0.091	-0.022	-0.056	-0.105	0.164
	(-3.85)	(-3.79)	(-2.52)	(-0.41)	(-0.85)	(-2.64)	(2.22)
High	-0.223	-0.183	-0.147	-0.079	-0.156	-0.157	0.067
	(-2.88)	(-3.17)	(-2.58)	(-0.95)	(-1.77)	(-2.50)	(0.78)
Col. avg.	-0.177	-0.104	-0.073	0.001	0.041	-0.062	0.218
	(-3.48)	(-2.97)	(-2.32)	(0.03)	(0.82)	(-1.81)	(3.48)
High-Low	-0.136	-0.158	-0.158	-0.198	-0.441	-0.218	
	(-1.31)	(-1.71)	(-1.73)	(-1.76)	(-3.39)	(-2.21)	

Table 4: Raw return affects future fund performance (regressions): At the end of each month t, I form portfolios by sorting funds into buckets by variables measured over the past 12 months. In the first two columns, I sort funds into quintiles, first by fund alpha and then by fund raw return (column (1)) and fund's past realized flow (column (2)). This yields 25 portfolios at each date. In column (3), I sort funds into quartiles, first by past alpha, then by past raw return, and then by past realized flow. This yields 64 portfolios at each date. In column (4), I sort into quintiles by fund alpha and then by the raw return (over the last 12 months) of the stock portfolio the fund held at date t. In column (5), I sort into quartlies by fund alpha, fund raw return, and raw return of the fund's stock portfolio. The dependent variable is always $\alpha^{fund}_{t+1:t+12}$, the fund alpha in the year after ranking. Independent variables are within-portfolio averages (with the top and bottom observations winsorized). Newey-West t-statistics are in parentheses. The sample period for columns not involving flow is 1980-2009, for columns involving flow it is 1991-2009.

Dependent variable	$\alpha^{fund}_{t+1:t+12}$				
	(1)	(2)	(3)	(4)	(5)
Past alpha $\alpha^{fund}_{t-11:t}$	0.2437	0.1203	0.2932	0.1625	0.2407
	(4.90)	(3.16)	(3.68)	(6.22)	(4.78)
Past raw return $R^{fund}_{t-11:t}$	-0.0102		-0.0146		-0.0125
	(-2.53)		(-2.58)		(-2.91)
Past realized flow		-0.0085	-0.0049		
		(-0.88)	(-0.66)		
Past raw return on ranking-date stock portfolio				-0.0019	0.0015
				(-1.20)	(0.82)
Expense ratio	-0.0701	-0.0174	0.0036	-0.0127	0.0074
	(-1.03)	(-0.20)	(0.05)	(-0.17)	(0.14)
Turnover ratio	0.0008	-0.0000	0.0006	0.0004	0.0004
	(1.58)	(-0.01)	(0.99)	(0.89)	(1.15)
Log(age)	0.0003	-0.0002	0.0000	-0.0001	0.0000
	(0.72)	(-0.63)	(0.02)	(-0.24)	(-0.10)
Log(size)	-0.0005	-0.0002	-0.0002	-0.0005	-0.0003
	(-3.11)	(-0.91)	(-1.50)	(-2.05)	(-2.25)
Log(family size)	0.0000	0.0000	0.0000	0.0000	0.0000
	(1.56)	(-0.75)	(1.25)	(1.14)	(2.19)
Number of portfolios at each date	25	25	64	25	64
Portfolios formed by sorting on fund alpha and:	fund raw return	fund realized flow	fund raw return fund realized flow	stock raw return	fund raw return stock raw return

Table 5: Aggregate unsophisticated-flow-induced trades of the portfolio the fund holds affects future fund alpha (regressions): At the end of each month, I form portfolios by sorting funds into terciles sequentially by (1) the fund's past 12 months' alpha, (2) the fund's past 12 months' raw return, (3) the aggregate sales, by low raw return funds, of the stock portfolio the fund held on the ranking date, and (4) the aggregate buys, by high raw return funds, of the stock portfolio the fund held on the ranking date. This yields 81 portfolios at each date, which I use to run Fama-MacBeth regressions. In columns (1)-(6), the dependent variable is $\alpha^{fund}_{t+1:t+12}$: the alpha of the fund portfolio in the year after ranking. In column (7), the dependent variable is the alpha of the ranking-date portfolio $\alpha^{RDP}_{t+1:t+12}$: the alpha, in the year after ranking, of the stock portfolio the fund held on the ranking date. Dependent variables are within-portfolio averages (with the top and bottom observations winsorized). Newey-West t-statistics are in parentheses. The sample period is 1980-2009.

Dependent variable	$\alpha^{fund}_{t+1:t+12}$						$\alpha^{RDP}_{t+1:t+12}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Past alpha $\alpha^{fund}_{t-11:t}$	0.2348	0.1357	0.2320	0.1322	0.1469	0.1006	0.0538
	(4.61)	(3.70)	(3.85)	(3.11)	(3.24)	(5.83)	(1.15)
Past raw return $R_{t-11:t}$	-0.0114	-0.0030	-0.0116	-0.0020	-0.0044	-0.0035	0.0002
	(-2.92)	(-1.03)	(-2.68)	(-0.67)	(-1.49)	(-2.46)	(0.09)
Agg. sales by low raw return funds		-0.0036			-0.0033	-0.0006	-0.0033
		(-3.48)			(-3.41)	(-1.06)	(-2.77)
Agg. buys by high raw return funds			0.0009		0.0007	0.0006	-0.0006
			(0.55)		(0.42)	(0.82)	(-0.21)
Agg. net buys assoc. with raw returns				-0.0023			
				(-4.22)			
Alpha of ranking-date stock portfolio						0.7919	
(in year after ranking) $\alpha^{RDP}_{t+1:t+12}$						(52.25)	
Expense ratio	-0.0294	-0.0432	-0.0237	-0.0156	-0.0426	-0.0492	0.0042
	(-0.57)	(-0.96)	(-0.52)	(-0.35)	(-1.22)	(-3.71)	(0.11)
Turnover ratio	0.0013	0.0007	0.0010	0.0009	0.0006	0.0003	0.0004
	(1.84)	(1.46)	(1.82)	(1.60)	(1.58)	(1.56)	(1.42)
Log(age)	-0.0001	0.0002	-0.0001	0.0002	0.0002	0.0000	0.0002
	(-0.15)	(0.54)	(-0.30)	(0.80)	(0.75)	(-0.13)	(1.09)
Log(size)	-0.0003	-0.0003	-0.0002	-0.0002	-0.0003	-0.0001	-0.0002
	(-2.47)	(-2.64)	(-2.06)	(-2.13)	(-2.31)	(-2.67)	(-1.78)
Log(family size)	0.0001	0.0000	0.0001	0.0001	0.0000	0.0000	0.0000
	(2.04)	(1.63)	(2.28)	(2.03)	(1.92)	(3.90)	(-0.34)
Difference between the coefficients					0.0010		
on raw return (cols. (5) and (6))					(0.41)		
Difference between the coefficients					0.0028		
on aggregate sales (cols. (5) and (6))					(2.92)		
Difference between the coefficients					-0.0001		
on aggregate buys (cols. (5) and (6))					(-0.07)		

Table 6: Aggregate unsophisticated-flow-induced trades of the portfolio the fund holds affects future fund alpha (portfolios) : Fund four-factor alphas (percent p.m.), net of fees, for portfolios formed at the end of each month by sequentially sorting funds on their past twelve months' four-factor alpha and the aggregate unsophisticated-flow-induced trades of the stock portfolio the fund held on the ranking date. Portfolios are held for 12 months after formation. White t-statistics are in parentheses. The sample period is 1980-2009.

Panel A: Sorting on aggregate sales, by low raw return funds, of the portfolio the fund held on the ranking date

	Past alpha quintile						
	Low	2	3	4	High	Row Avg.	High-Low
Aggregate sales quintile							
Low	-0.063	0.015	0.032	0.125	0.261	0.074	0.324
	(-0.68)	(0.20)	(0.44)	(1.57)	(2.66)	(0.93)	(4.93)
2	-0.102	-0.070	-0.042	0.043	0.151	-0.004	0.253
	(-1.54)	(-1.30)	(-0.85)	(0.81)	(2.34)	(-0.08)	(3.83)
3	-0.145	-0.115	-0.049	-0.043	0.080	-0.054	0.225
	(-2.57)	(-2.91)	(-1.46)	(-1.13)	(1.30)	(-1.60)	(2.94)
4	-0.211	-0.132	-0.107	-0.063	-0.033	-0.109	0.178
	(-3.88)	(-4.57)	(-3.69)	(-1.78)	(-0.53)	(-3.44)	(2.50)
High	-0.256	-0.163	-0.152	-0.116	-0.138	-0.165	0.117
	(-3.70)	(-3.41)	(-3.43)	(-1.98)	(-1.76)	(-3.11)	(1.76)
Col. avg.	-0.156	-0.093	-0.064	-0.011	0.064	-0.052	0.220
	(-3.00)	(-2.53)	(-1.96)	(-0.30)	(1.23)	(-1.46)	(3.70)
High-Low	-0.193	-0.178	-0.184	-0.241	-0.400	-0.239	
	(-1.58)	(-1.80)	(-1.91)	(-2.14)	(-2.79)	(-2.18)	

Panel B: Sorting on aggregate buys, by high raw return funds, of the portfolio the fund held on the ranking date

	Past alpha quintile						
	Low	2	3	4	High	Row Avg.	High-Low
Aggregate buys quintile							
Low	-0.152	-0.050	-0.013	0.057	0.195	0.008	0.347
	(-1.98)	(-0.73)	(-0.21)	(0.91)	(2.62)	(0.13)	(5.57)
2	-0.123	-0.086	-0.078	0.004	0.148	-0.027	0.270
	(-2.07)	(-1.87)	(-1.78)	(0.08)	(2.92)	(-0.65)	(4.17)
3	-0.155	-0.117	-0.068	-0.015	0.019	-0.067	0.174
	(-2.70)	(-3.00)	(-2.17)	(-0.37)	(0.32)	(-2.00)	(2.42)
4	-0.170	-0.117	-0.079	-0.051	-0.009	-0.085	0.162
	(-2.79)	(-2.74)	(-2.10)	(-1.08)	(-0.12)	(-1.90)	(2.28)
High	-0.177	-0.095	-0.076	-0.049	-0.028	-0.085	0.149
	(-2.23)	(-1.44)	(-1.22)	(-0.69)	(-0.33)	(-1.26)	(2.08)
Col. avg.	-0.156	-0.093	-0.064	-0.011	0.064	-0.052	0.220
	(-3.00)	(-2.53)	(-1.96)	(-0.30)	(1.23)	(-1.46)	(3.70)
High-Low	-0.025	-0.044	-0.063	-0.106	-0.223	-0.093	
	(-0.22)	(-0.41)	(-0.61)	(-0.99)	(-1.89)	(-0.88)	

Table 7: Aggregate unsophisticated-flow-induced trades of the stocks a fund currently holds affects the future performance of those stocks: I replace each fund's return by the return of the stock portfolio it held on the ranking date, and then calculate and report 4-factor alphas (percent p.m.) using these returns. At the end of each month, I form fund portfolios by sequentially sorting funds on past 12 months' 4-factor alpha and past aggregate unsophisticated flow driven trades. Portfolios are held for 12 months after formation. White t-statistics are in parentheses. The sample period is 1980-2009.

Panel A: Sorting on aggregate sales, by low raw return funds, of the portfolio the fund held on the ranking date

	Past alpha quintile						
	Low	2	3	4	High	Row Avg.	High-Low
Aggregate sales quintile							
Low	0.059	0.091	0.088	0.146	0.242	0.125	0.183
	(0.55)	(1.03)	(1.04)	(1.60)	(2.13)	(1.35)	(2.56)
2	-0.007	0.016	0.042	0.065	0.141	0.051	0.148
	(-0.10)	(0.27)	(0.75)	(1.12)	(2.01)	(0.91)	(2.05)
3	-0.052	-0.011	0.023	0.043	0.102	0.021	0.154
	(-0.92)	(-0.25)	(0.56)	(1.03)	(1.63)	(0.58)	(1.83)
4	-0.094	-0.027	-0.011	0.022	0.002	-0.021	0.096
	(-1.69)	(-0.81)	(-0.32)	(0.56)	(0.03)	(-0.63)	(1.15)
High	-0.127	-0.058	-0.044	-0.054	-0.085	-0.073	0.043
	(-1.78)	(-1.09)	(-0.89)	(-0.88)	(-0.94)	(-1.25)	(0.58)
Col. avg.	-0.045	0.002	0.020	0.044	0.080	0.020	0.125
	(-0.83)	(0.05)	(0.52)	(1.13)	(1.42)	(0.53)	(1.84)
High-Low	-0.186	-0.149	-0.132	-0.200	-0.326	-0.198	
	(-1.35)	(-1.30)	(-1.16)	(-1.54)	(-1.97)	(-1.54)	

Panel B: Sorting on aggregate buys, by high raw return funds, of the portfolio the fund held on the ranking date

	Past alpha quintile						
	Low	2	3	4	High	Row Avg.	High-Low
Aggregate buys quintile							
Low	-0.041	0.037	0.074	0.101	0.205	0.075	0.245
	(-0.46)	(0.47)	(0.98)	(1.34)	(2.39)	(0.99)	(3.84)
2	-0.023	0.019	0.007	0.057	0.153	0.043	0.177
	(-0.35)	(0.36)	(0.13)	(1.06)	(2.75)	(0.89)	(2.39)
3	-0.044	-0.006	0.020	0.046	0.036	0.010	0.080
	(-0.73)	(-0.14)	(0.56)	(1.13)	(0.59)	(0.28)	(0.98)
4	-0.052	-0.011	0.004	0.003	-0.004	-0.012	0.048
	(-0.86)	(-0.24)	(0.10)	(0.07)	(-0.06)	(-0.26)	(0.59)
High	-0.062	-0.026	-0.005	0.014	0.016	-0.012	0.078
	(-0.79)	(-0.39)	(-0.07)	(0.19)	(0.16)	(-0.17)	(1.07)
Col. avg.	-0.045	0.002	0.020	0.044	0.080	0.020	0.125
	(-0.83)	(0.05)	(0.52)	(1.13)	(1.42)	(0.53)	(1.84)
High-Low	-0.022	-0.063	-0.079	-0.087	-0.189	-0.088	
	(-0.17)	(-0.53)	(-0.67)	(-0.70)	(-1.37)	(-0.72)	

Table 8: Effect of aggregate trades by funds with low and high raw returns and funds with low and high flows on future fund alpha: At the end of each month, I form portfolios by sorting funds into quartiles sequentially by (1) the fund's past 12 months' alpha, (2) the fund's past 12 months' raw return, and then into terciles by (3) the sum of all sales variables for the stock portfolio the fund held on the ranking date, and (4) the sum of all buys variables for the stock portfolio the fund held on the ranking date. This yields 144 portfolios at each date, which I use to run Fama-MacBeth regressions. In all columns, the dependent variable is $\alpha^{fund}_{t+1:t+12}$: the monthly alpha of the fund portfolio in the year after ranking. Dependent variables are within-portfolio averages (with the top and bottom observations winsorized). Newey-West t-statistics are in parentheses. Sample period is 1991-2009.

Dependent variable	$\alpha^{fund}_{t+1:t+12}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Past alpha $\alpha^{fund}_{t-11:t}$	0.2837	0.1665	0.2141	0.1849	0.2482	0.1715	0.1730
	(3.61)	(2.36)	(2.44)	(2.44)	(2.63)	(2.17)	(2.22)
Past raw return $R_{t-11:t}$	-0.0140	-0.0045	-0.0088	-0.0069	-0.0100	-0.0046	-0.0049
	(-2.48)	(-0.90)	(-1.52)	(-1.45)	(-1.90)	(-1.04)	(-1.03)
Aggregate buys by funds with							
High raw return, high flow		0.0000		-0.0001		-0.0001	-0.0002
		(-0.08)		(-0.86)		(-0.69)	(-1.54)
High raw return, low flow			-0.0014	0.0047			0.0024
			(-0.24)	(0.95)			(0.47)
Low raw return, high flow					0.0002	0.0000	0.0001
					(2.09)	(0.24)	(0.83)
Low raw return, low flow							0.0001
							(0.50)
Aggregate sales by funds with							
High raw return, high flow							0.0000
							(-0.26)
High raw return, low flow					-0.0001	-0.0001	-0.0001
					(-1.55)	(-1.36)	(-1.30)
Low raw return, high flow			-0.0004	0.0001			0.0002
			(-1.66)	(1.01)			(1.58)
Low raw return, low flow		-0.0003		-0.0003		-0.0002	-0.0002
		(-2.41)		(-2.33)		(-2.60)	(-2.71)
Expense ratio	0.0387	-0.0150	-0.0229	-0.0366	-0.0238	-0.0430	-0.0517
	(0.44)	(-0.28)	(-0.48)	(-0.96)	(-0.46)	(-1.14)	(-1.77)
Turnover ratio	0.0007	0.0003	0.0003	0.0003	0.0005	0.0003	0.0003
	(1.06)	(0.63)	(0.70)	(0.67)	(0.95)	(0.76)	(0.79)
Log(age)	0.0000	0.0002	0.0000	0.0001	0.0000	0.0001	0.0001
	(0.06)	(0.92)	(0.02)	(0.66)	(0.20)	(0.90)	(0.85)
Log(size)	-0.0002	-0.0002	-0.0002	-0.0001	-0.0002	-0.0001	-0.0001
	(-1.38)	(-1.40)	(-1.77)	(-1.35)	(-1.94)	(-1.30)	(-1.61)
Log(family size)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(1.70)	(1.55)	(0.11)	(1.12)	(0.57)	(1.67)	(1.15)

Appendix A List of CRSP fund styles used

I use three style definitions. Before 1992, I use the Wiesenberger style codes. From 1993 to 1999, I use the Strategic Insight objective codes. From 1999 to 2007, I use the Lipper objective codes.

Wiesenberger	G, G-S, GRO, LTG, G-I, I-G, G-I-S, I-G-S, I-S-G, S-G-I, S-I-G, GRI, GCI, I, I-S, IEQ, ING, MCG, ENR, FIN, HLT, TCH, UTL, SCG, AGG
Strategic Insight	GRI, GRO, ING, AGG, SCG, FLX, GMC, NTR, FIN, HLT, TEC, UTL
Lipper	G, EI, CA, SG, FX, MC, NR, FS, H, TK, UT

Appendix B Supplementary results

B.1 DGTW fails to adequately control for UMD exposure across fund portfolios sorted by raw return

I adjust fund returns following the DGTW procedure, and then run the four-factor model on the adjusted returns. If the DGTW procedure adequately controls for UMD exposure, then the UMD betas of the high-raw-return funds should be the same as the UMD betas of the low raw return funds – zero.

I download the portfolio assignments and the benchmark portfolio returns from Russ Wermers' website[29]. Wermers (2004) sorts stocks into quintiles sequentially by size, book-to-market, and momentum measured in June of every year, yielding 125 benchmark portfolios. This sort would, by construction, control for momentum loading best in July, and with decreasing accuracy in the rest of the year. To improve the benchmark, I reform the 125 portfolios each month[30]. At the end of each month, within Wermers' 25 size and book-to-market buckets, I sort stocks into quintiles based on their prior 12 month return (leaving a month's gap). The benchmark portfolios so formed are highly correlated with DGTW's benchmarks in July, and less and less correlated over the year, as expected. For each fund in each month, I calculate the DGTW-adjusted returns in the standard way.

As in my base result, I then sort funds into quintiles by past alpha and past raw return, and hold these portfolios for 12 months. Using the Jegadeesh and Titman (1993) method, I get a single time-series of DGTW-adjusted returns for each bucket. I then run these time-series on the Fama-French-Carhart factors. In table B.1, I report the UMD betas of my alpha and raw return sorted portfolios.

If the DGTW adjustment procedure adequately controls for factor loadings, these adjusted portfolio returns should have zero betas. In actual fact I find that some portfolios' adjusted returns exhibit significant UMD betas, and, more seriously, the UMD betas of low raw return funds are much more negative than the betas of high raw return funds. This difference is strongly significant in every alpha quintile. This leads me to conclude that the DGTW procedure does not adequately control for UMD loadings in my portfolios.

[29]http://www.rhsmith.umd.edu/faculty/rwermers/ftpsite/dgtw/coverpage.htm

[30]The results in Table B.1 strengthen if I use the downloaded benchmarks and assignments.

B.2 Measurement error in ranking-year alphas from time-varying UMD betas

There is a specific way in which measurement error might arise in my context. Figure 2 shows that high-raw return funds have momentum betas that increase over the ranking year (and then fall). Estimating a Carhart model using data over the 24 months before the ranking date assumes a constant set of betas over these months, and so the momentum beta over the last few months of the ranking year will be underestimated. This may result in ranking-year alphas for these funds being overestimated.

To demonstrate that this is not driving the results, I create new estimates of the alphas of the portfolios during the ranking year that are not affected by the variation in the betas around the ranking date. For each of my 25 buckets, I construct a single portfolio return time-series as follows. Consider the funds placed in the high-alpha high-raw return bucket in the ranking at the end of December 2000. Call the equal weighted portfolio of these funds the *ranked portfolio* for December 2000. The portfolio I actually hold in November 2000 is the equal-weighted average of the ranked portfolios for December 2000 to November 2001. Doing this for each month yields a single time-series of portfolio returns for this bucket. I can then run a factor model on this time-series of returns, and calculate an alpha. This alpha has the interpretation of the average alpha of the funds in this bucket in the twelve months before ranking. This estimate is unaffected by variation in factor loadings around the ranking date. This approach is identical to the usual Jegadeesh and Titman (1993) approach, except that it is run backwards from the ranking date.

I repeat the procedure for each of my buckets, and report results in Table B.2. In each alpha quintile, the difference in ranking-year alphas between funds with high and low raw return is always positive and significant. This means that the high-raw return funds (for instance) have *more*, not less, skill than is evident from their short-horizon alphas. If there is a bias, these results suggest that the bias runs in the wrong direction to be driving my results.

B.3 The effect of aggregate unsophisticated-flow induced trades on high-alpha funds

I started by showing that raw return is negatively related to future alphas, and then showed that, in the whole sample, this is largely due to the effect of sales by funds with low raw returns. I now examine high-alpha funds separately. High-alpha funds are particularly interesting for two reasons. First, these are most likely to have positive future alphas, and will therefore enter any fund-based trading strategy. Second, the portfolio results indicate that the effects I examine are strongest among high-alpha funds.

I rerun the regression analysis focussing only on the funds in the highest tercile by fund alpha. I report results in Table B.3, which is identical in construction to Table 5. As in that table, I sort funds into terciles sequentially by past fund alpha, past fund raw return (orthogonalized relative to alpha), aggregate unsophisticated-flow induced sales and aggregate unsophisticated-flow induced buys, but I only keep the highest alpha tercile. This gives me $1 \times 3 \times 3 \times 3 = 27$ portfolios at each date, instead of 81 as in Table 5. Once again, in columns 2, 3 and 5, aggregate unsophisticated-flow induced sales are significant, while aggregate unsophisticated-flow induced buys are not. I conclude flow-induced trades increase the appearance of performance persistence among high-alpha funds.

It is notable that these funds all have high alphas, and so, ex ante, I would not expect them to be affected by the sales of funds with unsophisticated outflows. While the funds themselves may not have sold stocks, my results indicate the *stocks* in their portfolios may be affected by the sales of *other* funds with unsophisticated outflow.

The notable difference between Table 5 and this table is the fact that fund raw return remains significant as a predictor of fund performance, even controlling for aggregate sales (columns 2, 4, and 5). I take this to mean that among high-alpha funds, raw return itself *does* have an impact on future fund performance.

What is the mechanism through which this happens? One possibility is that raw return affects future performance via the prices of the underlying stocks, but this effect is not captured by my aggregate trade measures. In column 7, I study the portfolio the fund held on the ranking date, and I find that raw return has no effect on that portfolio's performance. Moreover, raw return remains significant as a predictor of fund performance even when controlling for the alpha of that portfolio (column 6). Thus, raw return appears to affect the performance of these funds in a way that has little to do with flow-driven price pressure – that is, it changes something about the fund itself, rather than altering the behavior of the stocks the fund holds. This suggests a role for other mechanisms through which flows affect performance – for example, diseconomies of scale.

Finally, I check if the coefficients on the flow variables are significantly different in the top tercile of funds, compared to their values estimated using the bottom two terciles. For concreteness, I focus on the models of columns 4 and 5. In column 4, which uses aggregate net buys as a predictor, I find that the coefficient on aggregate net buys is -0.0025 in the top tercile, while its value in the same regression in the bottom two terciles is -0.0024 (t-statistic 4.23). The difference is 0.00004, with a t-statistic of 0.09. So the effect of aggregate net buys is not different for funds in the top alpha tercile. In contrast the coefficient on raw return is different for these funds: it is -0.00632 in the top tercile, and almost exactly 0 in the bottom two terciles. The difference is 0.00632, with a t-statistic of 2.15.

I find a similar result looking at sales separately (in the model of column 5). In the top alpha tercile, I find the coefficient on aggregate sales is -0.0035. In the bottom two terciles, its value is -0.0036. The difference is -0.0001, with a t-statistic of 0.17. Again in contrast, for raw returns, the coefficient in the top tercile is -0.0085 (t-statistic 2.45), while the coefficient in the bottom two terciles is -0.0035 (t-statistic 1.03). The difference is 0.005 (t-statistic 1.5).[31]

I conclude that raw returns appear to affect funds in the highest alpha tercile differently from the rest of the funds. The trade measures appear to affect all funds the same way[32]. The fact that funds with higher alphas are being subject to two correlated but distinct effects may explain why my results appear stronger among such funds.

B.4 Decomposition of fund alphas

My results suggest that all the predictive power of aggregate unsophisticated-flow induced sales is through its impact on the portfolio the fund held on the ranking date. This follows from a comparison of columns 5 and 6 of Table 5. I could also examine this in a portfolio context. A simple way to do this is to decompose fund performance in the year after ranking into two components: one that comes from the portfolio held on the ranking date, and one that comes from changes made since then.

The purpose of this decomposition is to establish, in a portfolio context, how much of the alpha of the fund in the holding year (that is, the year after ranking) is due to the portfolio held by the fund before the ranking date. If a majority of the alpha is due to that portfolio, it will confirm earlier results: that the mechanism which causes, for example, funds with large aggregate sales to have high subsequent returns is not that they make good stock picks or incur lower costs *after* they get flows. Instead, the funds do well because the stock portfolios they have chosen at some time in the past do well.

Suppose there are N stocks in the market. Let t be a particular ranking date. Let H_s be the $N \times 1$ vector of the number of shares held by a particular fund at the end of month s. Thus, H_t is a vector of the number of shares of each stock held by the fund on the ranking date. Let $\Delta_{r,s}$ be the change in shares held between the end of month r and the end of month s. By definition,

$$H_{t+j-1} = H_t + \Delta_{t,t+j-1}$$

[31] As an alternative, I compare the results from the top tercile with the results in the entire sample, that is, I compare the results in Table 5 with those in Table B.3. In both columns 4 and 5, I find that the coefficient on raw return is significantly more negative in the top tercile – the differences (t-statistics) are -0.0043 (2.14) for column 4 and -0.0040 (1.79) for column 5 – while the aggregate trade measures are, again, not different.

[32] This is expected, because the trade measures are to do with the stocks the funds hold, rather than anything to do with the funds themselves. However, this is not necessarily the whole story. The point estimates indicate that the effect of aggregate sales on the stock portfolio the fund held on the ranking date is somewhat larger among funds with high alphas. This can be seen by comparing the coefficient on aggregate sales in column 7 of Table B.3 with the analogous number in Table 5. The number is -0.0033 in the former table and -0.0047 in the latter. However, the difference is not significant.

I am interested in returns over the twelve months after ranking, that is, earned by portfolios H_{t+j-1} over $j = 1$ to $j = 12$[33].

Let P_s be the $N \times 1$ vector of prices of the N stocks at the end of month s. Let R_s be the $N \times 1$ vector of returns of the N stocks over month s.

Let $R_{t+j}^{underlying}$ be the return on the fund's underlying stock portfolio over month $t+j$. We can write

$$R_{t+j}^{underlying} = \frac{(P_{t+j-1} \cdot H_{t+j-1})' R_{t+j}}{(P_{t+j-1} \cdot H_{t+j-1})' \mathbf{1}}$$

where $(\cdot)$ indicates element-by-element multiplication, and $\mathbf{1}$ is a vector of ones.

Similarly let $R_{t,t+j}^{old}$ be the return that would have been obtained in month $t+j$ on the stock portfolio held at the end of month t had the portfolio not been changed. We can write this term as

$$R_{t,t+j}^{old} = \frac{(P_{t+j-1} \cdot H_t)' R_{t+j}}{(P_{t+j-1} \cdot H_t)' \mathbf{1}}$$

Let $R_{t,t+j}^{change}$ be the return in month $t+j$ on the stock portfolio $\Delta_{t,t+j-1}$. We can write this term as

$$R_{t,t+j}^{change} = \frac{(P_{t+j-1} \cdot \Delta_{t,t+j-1})' R_{t+j}}{(P_{t+j-1} \cdot \Delta_{t,t+j-1})' \mathbf{1}}$$

The fund's current portfolio can be thought of as a portfolio of two assets: the portfolio held unchanged from t, and the portfolio consisting of the changes made between t and today. Define

$$\omega_{t,t+j-1}^{old} = \frac{(P_{t+j-1} \cdot H_t)' \mathbf{1}}{(P_{t+j-1} \cdot H_{t+j-1})' \mathbf{1}}$$

the fraction of the portfolio at date $t+j$ that is invested in the portfolio that was held at t.

Similarly, define

$$\omega_{t,t+j-1}^{change} = \frac{(P_{t+j-1} \cdot \Delta_{t,t+j-1})' \mathbf{1}}{(P_{t+j-1} \cdot H_{t+j-1})' \mathbf{1}}$$

the fraction of the portfolio at date $t+j$ that is invested in the stocks other than the portfolio known to have been held at t. Then I can write

$$R_{t+j}^{underlying} = \omega_{t,t+j-1}^{old} R_{t,t+j}^{old} + \omega_{t,t+j-1}^{change} R_{t,t+j}^{change} \tag{2}$$

OLS coefficients are linear in the dependent variable. Therefore, if I estimate two factor model

[33] H_t is the holdings on the ranking date, on which the return in the first month after ranking ($j = 1$) are earned.

using the same factors as independent variables, and, as dependent variables, first, $\omega^{old}_{t,t+j-1}(R^{old}_{t,t+j} - R_f)$, and next, $\omega^{change}_{t,t+j-1}(R^{change}_{t,t+j} - R_f)$, the alphas I get from these two regressions will add up to the factor alpha on the fund's underlying portfolio.

I report the results of the decomposition in Table B.4. In constructing this table, I eliminate some fund-months in which the assets change by a factor of 100 in either direction between the month of the *old* portfolio and the month before the month of the return. Leaving these in creates large outliers in the *change* portfolio's weights. Additionally, I eliminate fund-months in which the fund holds fewer than 10 stocks. Since all eliminations are made before the returns are earned, there is no obvious bias.

A subtlety is that I only retain observations in which the fund report used to generate the "underlying" portfolio – the portfolio the fund most recently reported holding – is not the same one as that used to generate the "old" portfolio – the last reported portfolio on or before the ranking date[34]. This weakens the connection between the "underlying" and "old" portfolios, and under the null hypothesis of no relation between these two, biases my results towards not finding anything.

Panel A of Table B.4 reports the unconditional 4-factor alphas on the funds' underlying portfolios. The alphas of these (stock) portfolios show the same patterns as were present in the alphas of the funds. This is not surprising and merely means that my results are not driven by the "return gap" of Kacperczyk et al. (2008)[35]. I observe that the difference between high and low aggregate sales funds is negative, and significant in every alpha quintile.

In Panel B of Table B.4, I present the portion of the underlying portfolio's alpha which is attributable to the *old* portfolio, and in Panel C, I present the contribution from the *change* portfolio. The pattern in alphas is replicated in Panel B. In each column, this component of fund alpha decreases monotonically in the aggregate unsophisticated-flow induced sales. The differences between the high- and low-aggregate sales funds are large and significant in four out of five alpha quintiles. The point estimates indicate that, on average, 93% (i.e., 25.5 of 27.5 bp) of the aggregate-sales-related spread in fund performance can be attributed to this old portfolio.

Looking at the *change* component in Panel C, I observe that this component is much smaller than the *old* component in magnitude. For example, the largest difference in this component between high- and low-aggregate sales funds is 5.6 bp (in the highest alpha quintile). The corre-

[34]Consider the ranking date of 31 December 2000. Suppose that the fund filed a holding report on 30 November 2000, and another on 28 February 2001. I would not include return observations from January and February 2001 when I construct the returns for this fund for the 12 months after this ranking date, because on those dates the "old" and "underlying" portfolios would be identical.

This procedure means that the first month after ranking is always dropped, since for that month the "old" and "underlying" portfolios are identical.

[35]Kacperczyk et al. (2008) define the return gap as the difference between the return on the fund and the return on the portfolio the fund most recently reported holding.

sponding number in Panel B is 35.8 bp. The differences between the high- and low-aggregate sales funds are never significant.

I have shown earlier that performance only appears to persist among high alpha funds with low aggregate sales and low alpha funds with high aggregate sales. It is instructive to calculate how much of this apparent persistence is due to the "old" portfolio and how much due to changes made. From Panel A, the difference between the future alpha of the high-alpha, low aggregate buys funds and that of the low-alpha, high aggregate buys funds is 44.6 bp/month ($= 40.1 - (-4.5)$), with a t-statistic of 3.12 (this statistic is not shown in the table). Of this spread, 35.1 bp/month, or 79%, is attributable to the old portfolio, and this component is significantly positive (t-statistic 2.06). The remaining 9.5 bp/month is attributable to the change portfolio, and this component is insignificant (t-statistic 1.26).

I conclude that aggregate sales affect fund performance principally through their effect on the stock portfolio the fund held on the ranking date.

Table B.1: UMD betas for DGTW-adjusted returns: At the end of each month, I sort funds into quintiles by past 12 months' 4-factor alpha and past 12 months' raw return (orthogonalized to alpha), giving 25 buckets. I use the DGTW procedure to adjust returns for stock characteristics. I form a single portfolio time-series for each of the 25 buckets, using the Jegadeesh and Titman (1993) method. I run the adjusted time-series of portfolio returns on the 4 Fama-French-Carhart factors. I report the UMD betas from these regressions. The sample period is 1980-2009.

Panel A: UMD betas for portfolios formed by sorting on past raw return

	Past alpha quintile						
	Low	2	3	4	High	Row Avg.	High-Low
Past raw return quintile							
Low	-0.100	-0.073	-0.060	-0.059	-0.099	-0.078	0.001
	(-4.33)	(-3.89)	(-3.70)	(-3.41)	(-3.81)	(-3.97)	(0.06)
2	-0.050	-0.022	-0.018	-0.018	-0.036	-0.029	0.014
	(-3.66)	(-2.32)	(-1.99)	(-1.88)	(-2.85)	(-2.84)	(1.37)
3	-0.024	-0.009	-0.010	-0.008	-0.011	-0.012	0.013
	(-2.45)	(-1.42)	(-1.52)	(-1.18)	(-0.89)	(-1.93)	(0.83)
4	-0.007	0.000	-0.001	0.002	0.011	0.001	0.018
	(-0.93)	(-0.08)	(-0.09)	(0.19)	(0.68)	(0.10)	(1.07)
High	0.018	0.016	0.010	0.013	0.057	0.023	0.039
	(1.51)	(1.58)	(0.90)	(0.87)	(2.86)	(1.81)	(2.35)
Col. avg.	-0.033	-0.018	-0.015	-0.014	-0.015	-0.019	0.017
	(-3.11)	(-2.38)	(-2.38)	(-1.93)	(-1.34)	(-2.51)	(1.42)
High-Low	0.118	0.089	0.070	0.073	0.156	0.101	
	(4.29)	(3.72)	(3.09)	(2.65)	(4.16)	(3.74)	

Table B.2: Robustness to variation in betas around the ranking date: I form portfolios formed by sorting funds on their past twelve months' four-factor alpha and past twelve months' raw return at the end of each month. I report the ranking-year (i.e., the 12 months before ranking) 4-factor alphas measured in a way that allows for variation in betas around the ranking date. White t-statistics are in parentheses. The sample period is 1980-2009.

Panel A: Ranking-year alphas measured without error							
	Past alpha quintile						
	Low	2	3	4	High	Row Avg.	High-Low
Past raw return quintile							
Low	-1.296	-0.816	-0.597	-0.420	-0.021	-0.630	1.275
	(-13.02)	(-9.77)	(-7.24)	(-4.93)	(-0.19)	(-7.26)	(14.99)
2	-0.938	-0.455	-0.241	-0.061	0.320	-0.274	1.258
	(-13.03)	(-9.18)	(-5.09)	(-1.27)	(5.42)	(-5.64)	(17.91)
3	-0.677	-0.224	-0.036	0.165	0.634	-0.027	1.311
	(-10.80)	(-5.77)	(-1.03)	(4.56)	(11.62)	(-0.77)	(16.53)
4	-0.438	-0.012	0.178	0.394	0.985	0.222	1.422
	(-7.32)	(-0.27)	(4.39)	(8.82)	(13.35)	(5.10)	(16.67)
High	-0.032	0.358	0.542	0.807	1.533	0.642	1.565
	(-0.33)	(4.73)	(7.57)	(10.24)	(11.97)	(7.65)	(16.27)
Col. avg.	-0.674	-0.228	-0.029	0.179	0.693	-0.012	1.367
	(-11.47)	(-5.92)	(-0.88)	(5.47)	(12.71)	(-0.32)	(18.95)
High-Low	1.264	1.174	1.139	1.227	1.554	1.272	
	(8.30)	(8.58)	(8.31)	(8.24)	(7.72)	(8.43)	

Table B.3: Aggregate unsophisticated-flow-induced trades of the portfolio the fund holds affects future fund alpha (regressions, only top tercile of past alpha): At the end of each month, I form portfolios by sorting funds into terciles sequentially by (1) the fund's past 12 months' alpha, (2) the fund's past 12 months' raw return, (3) the aggregate sales, by low raw return funds, of the stock portfolio the fund held on the ranking date, and (4) the aggregate buys, by high raw return funds, of the stock portfolio the fund held on the ranking date. In this table, I keep only the top tercile of funds by alpha. This yields 27 portfolios at each date, which I use to run Fama-MacBeth regressions. In columns (1)-(6), the dependent variable is $\alpha^{fund}_{t+1:t+12}$: the alpha of the fund portfolio in the year after ranking. In column (7), the dependent variable is the alpha of the ranking-date portfolio $\alpha^{RDP}_{t+1:t+12}$: the alpha, in the year after ranking, of the stock portfolio the fund held on the ranking date. Dependent variables are within-portfolio averages (with the top and bottom observations winsorized). Newey-West t-statistics are in parentheses. The sample period is 1980-2009.

Dependent variable	$\alpha^{fund}_{t+1:t+12}$						$\alpha^{RDP}_{t+1:t+12}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Past alpha $\alpha^{fund}_{t-11:t}$	0.3195	0.1895	0.3103	0.1940	0.1973	0.0761	0.1498
	(3.34)	(2.54)	(3.38)	(2.56)	(2.80)	(3.02)	(1.76)
Past raw return $R_{t-11:t}$	-0.0162	-0.0084	-0.0148	-0.0063	-0.0085	-0.0044	-0.0044
	(-3.70)	(-2.30)	(-3.28)	(-1.75)	(-2.45)	(-2.11)	(-1.13)
Agg. sales by low raw return funds		-0.0039			-0.0035	-0.0001	-0.0047
		(-3.26)			(-2.98)	(-0.19)	(-2.50)
Agg. buys by high raw return funds			-0.0001		-0.0008	0.0003	-0.0015
			(-0.06)		(-0.45)	(0.35)	(-0.81)
Agg. net buys assoc. with raw returns				-0.0025			
				(-3.84)			
Alpha of ranking-date stock portfolio						0.7871	
(in year after ranking) $\alpha^{RDP}_{t+1:t+12}$						(52.46)	
Expense ratio	0.0137	-0.0053	-0.0115	0.0076	-0.0259	-0.0453	0.0268
	(0.20)	(-0.09)	(-0.16)	(0.15)	(-0.47)	(-1.90)	(0.53)
Turnover ratio	0.0013	0.0006	0.0011	0.0007	0.0005	0.0005	0.0000
	(2.01)	(1.27)	(1.91)	(1.39)	(1.29)	(2.11)	(0.00)
Log(age)	0.0001	-0.0001	-0.0001	0.0000	-0.0003	-0.0002	-0.0001
	(0.31)	(-0.15)	(-0.33)	(-0.03)	(-0.80)	(-1.31)	(-0.30)
Log(size)	0.0000	-0.0001	-0.0001	0.0001	-0.0001	-0.0001	-0.0001
	(-0.27)	(-0.86)	(-0.37)	(0.46)	(-0.95)	(-0.70)	(-0.70)
Log(family size)	0.0000	0.0000	0.0001	0.0001	0.0000	0.0000	0.0000
	(0.90)	(0.57)	(1.39)	(1.25)	(1.26)	(2.43)	(-0.04)
Difference between the coefficients					0.0040		
on raw return (cols. (5) and (6))					(1.35)		
Difference between the coefficients					0.0034		
on aggregate sales (cols. (5) and (6))					(2.44)		
Difference between the coefficients					0.0011		
on aggregate buys (cols. (5) and (6))					(0.74)		

Table B.4: Decomposition of fund alphas: I decompose the unconditional 4-factor alpha on the fund's underlying portfolio into components from (1) the portfolio held on the ranking date (the *old* portfolio) and (2) the difference between the old portfolio and the portfolio currently held (the *change* portfolio). At the end of each month, I sequentially sort funds on past 4-factor alpha and past aggregate unsophisticated-flow-induced sales of the stock portfolios they currently hold. Portfolios are held for 12 months after formation. White t-statistics are in parentheses. The sample period is 1980-2009.

Panel A: Alphas of the underlying portfolios

	Past alpha quintile						
	Low	2	3	4	High	Row Avg.	High-Low
Aggregate sales quintile							
Low	0.206	0.257	0.263	0.313	0.401	0.284	0.195
	(1.57)	(2.17)	(2.29)	(2.64)	(2.96)	(2.35)	(2.78)
2	0.105	0.127	0.156	0.201	0.296	0.175	0.191
	(1.00)	(1.25)	(1.70)	(2.19)	(2.95)	(1.86)	(2.72)
3	0.052	0.075	0.108	0.150	0.218	0.126	0.166
	(0.53)	(0.87)	(1.44)	(1.87)	(2.31)	(1.56)	(2.00)
4	-0.008	0.050	0.065	0.090	0.100	0.061	0.108
	(-0.08)	(0.64)	(0.86)	(1.24)	(1.08)	(0.80)	(1.33)
High	-0.045	0.021	0.036	0.021	-0.014	0.009	0.031
	(-0.42)	(0.24)	(0.44)	(0.24)	(-0.13)	(0.11)	(0.39)
Col. avg.	0.063	0.105	0.132	0.152	0.201	0.130	0.138
	(0.66)	(1.21)	(1.65)	(1.91)	(2.28)	(1.59)	(2.10)
High-Low	-0.250	-0.236	-0.227	-0.292	-0.415	-0.275	
	(-1.92)	(-2.18)	(-2.07)	(-2.35)	(-2.57)	(-2.25)	

Panel B: Contribution from the portfolio held on the ranking date

	Past alpha quintile						
	Low	2	3	4	High	Row Avg.	High-Low
Aggregate sales quintile							
Low	0.294	0.256	0.229	0.253	0.350	0.275	0.056
	(1.94)	(2.01)	(1.93)	(2.03)	(2.23)	(2.11)	(0.57)
2	0.155	0.147	0.157	0.145	0.239	0.168	0.084
	(1.32)	(1.42)	(1.59)	(1.51)	(2.34)	(1.72)	(0.96)
3	0.112	0.093	0.160	0.131	0.160	0.135	0.048
	(0.97)	(1.06)	(1.83)	(1.64)	(1.70)	(1.65)	(0.46)
4	0.026	0.068	0.072	0.159	0.066	0.077	0.040
	(0.24)	(0.85)	(0.96)	(1.83)	(0.73)	(0.99)	(0.43)
High	-0.001	0.012	0.051	0.009	-0.008	0.020	-0.007
	(-0.01)	(0.13)	(0.61)	(0.11)	(-0.08)	(0.21)	(-0.08)
Col. avg.	0.123	0.112	0.142	0.138	0.163	0.136	0.040
	(1.17)	(1.27)	(1.72)	(1.72)	(1.85)	(1.62)	(0.54)
High-Low	-0.295	-0.245	-0.179	-0.244	-0.358	-0.255	
	(-1.77)	(-1.94)	(-1.52)	(-1.75)	(-1.93)	(-1.84)	

Panel C: Contribution from the changes made after the ranking date

	Past alpha quintile						
	Low	2	3	4	High	Row Avg.	High-Low
Aggregate sales quintile							
Low	-0.088	0.001	0.034	0.060	0.051	0.009	0.139
	(-1.75)	(0.03)	(1.23)	(1.78)	(0.74)	(0.33)	(1.78)
2	-0.050	-0.020	-0.001	0.056	0.057	0.007	0.107
	(-1.25)	(-0.88)	(-0.04)	(2.09)	(1.86)	(0.33)	(2.15)
3	-0.060	-0.018	-0.052	0.020	0.058	-0.009	0.118
	(-1.17)	(-0.85)	(-1.34)	(0.84)	(1.81)	(-0.51)	(2.00)
4	-0.034	-0.018	-0.008	-0.069	0.035	-0.017	0.068
	(-1.14)	(-1.15)	(-0.46)	(-1.59)	(1.30)	(-1.07)	(1.84)
High	-0.043	0.010	-0.015	0.012	-0.005	-0.010	0.038
	(-1.24)	(0.43)	(-0.88)	(0.49)	(-0.17)	(-0.53)	(0.93)
Col. avg.	-0.059	-0.007	-0.010	0.014	0.039	-0.005	0.098
	(-2.18)	(-0.44)	(-0.54)	(0.76)	(1.72)	(-0.37)	(2.76)
High-Low	0.045	0.009	-0.048	-0.048	-0.056	-0.020	
	(0.69)	(0.23)	(-1.53)	(-1.16)	(-0.74)	(-0.54)	