Follow the Leader: Peer Effects in Mutual Fund Portfolio Decisions

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Abstract

Mutual fund portfolio decisions depend on previous trades of other funds with outstanding past performance: funds mimic the mutual fund industry leaders. Controlling for other factors, for each dollar leaders invest in a given stock, the follower funds invest 15 to 30 cents in the subsequent quarter. Funds with poor past performance mimic more than funds with moderate performance; there is also some evidence that small and young funds mimic more than old and large ones. Leader trades that are likely to convey more information (more extreme trades, trades in more opaque stocks) elicit stronger responses. Mimicking makes economic sense: portfolios based on past trades of the leaders deliver significant 3 and 4 factor alphas of the order of 0.35% per month. Characteristics-matched returns indicate that a large portion of this abnormal performance is attributable to stock momentum, which suggests a possible link between "follow the leader" behavior and momentum.

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The present paper contributes to one of the most important questions in finance: how do we make our portfolio decisions? What determines the size and direction of our trades? Standard portfolio theory describes the weights of the optimal portfolio in terms of the expectations and the covariances of stock returns and important state variables. Because these inputs are never known with certainty, investors try to learn about them from many different sources. I propose that portfolio decisions of one's peers constitute such a source. If an investor learns about recent choices of other investors, he may tilt his portfolio towards their allocations. Moreover, the better the stock picking record of his peers, the higher his incentive to mimic them. In other words, I propose that investors "follow the leaders" in their portfolio decisions. As an example, the Wall Street Journal quotes[1] Douglas Davenport, the manager of Wisdom Fund, saying that he is "the only professional investor who is truly mimicking the holdings of the legendary investor Warren Buffett."

I test the "follow the leader" hypothesis using trades of mutual funds. This choice is motivated partly by data availability and partly by the fact that mutual funds are large, important, and some of the most sophisticated participants in the stock market. I test whether the trades of the best funds (the industry leaders) influence subsequent trades of other funds. As the information about leader trades becomes public through fund holding reports, interviews given to the media, etc., the remaining funds invest in the same securities. They are likely to do so with a lag, as they need time to find out what the leaders did.

For mimicking to arise, two conditions need to be met: some investors should be recognized as superior, and the information about their trades should at some stage become known to their peers. These conditions are likely satisfied for mutual funds.

It is plausible that at least some mutual fund managers believe that skill exists and would consider their well performing peers attractive mimicking targets. This belief would be in line with some recent academic studies (e.g., Bollen and Busse, 2005, Cohen, Coval, and Pastor, 2005, Spiegel, Mamaysky, and Zhang, 2005, or Wermers, 2003) that document short-term persistence of mutual fund performance, or with Berk and Green (2004) whose calibrated model implies that many fund managers have considerable skill. Moreover, individual investors seem to believe that skill exists in the mutual fund industry and chase funds with outstanding past performance (e.g., Chevalier and Ellison, 1997, Sirri and Tufano, 1998). Fund managers may behave in the same fashion and mimic the leaders' trades. The results presented here suggest that they do.

[1] Wall Street Journal, April 28, 2005.

The second condition, that trades of the leaders become known to other funds, is satisfied. In fact, it is in the interest of leader funds to make their portfolio decisions known as soon as they achieve their desired allocation. To the extent that other funds mimic their choices, potential price pressure will improve the leaders' returns. At the very least, follower funds can take advantage of portfolio composition reported to fund shareholders and to the SEC. Such reports, gathered and distributed by Thompson Financial, are used in this study. There are likely many other sources of information. They may include voluntary fund disclosures made at a higher frequency. Moreover, some managers, especially those with outstanding performance, are often featured in the media and sometimes publicly discuss their favorite stock bets. For instance, a CNN Money report, published on money.cnn.com on May 10, 2005, discusses the recent trades of Bill Miller, the star manager of Legg Mason Value Trust. The report also provides a link to the fund's website, which contains the portfolio composition from a recent SEC filing. Yet another source of information may be informal networks of fund managers. Hong, Kubik, and Stein (2005) provide evidence that such networks operate in large US cities. All these sources may help mutual funds copy the stock picks of their peers. Mimicking may in fact be possible even before holding reports are submitted to the SEC or released to the shareholders.

In the main tests presented here I classify funds as leaders and followers using their 4-factor Carhart alphas.[2] "Leaders" are funds with alphas in the top 5% of the cross-sectional distribution, while other funds are classified as potential "followers." A drawback of this definition is that it sometimes assigns the leader status to relatively unknown funds. It may be argued that such funds are not attractive mimicking targets. For this reason, I also present evidence based on the leaders from the Honor Roll of funds created annually by Forbes magazine. Forbes requires the funds in its ranking to be well established, well diversified, and have experienced managers. There is strong evidence of the "follow the leader" effect also for the Honor Roll leaders. Moreover, for this definition of leaders, the point estimates of the intensity of mimicking are about 50% higher than the estimates obtained for leaders defined by alphas. A possible explanation for this increase is that the Honor Roll funds get more media exposure than other funds and that it may be easier to mimic their trades.

I find that changes in leader portfolio weights are an important determinant of

[2]While most of the evidence presented here employs 4-factor alphas to define leaders, I have also used other performance measures, such as raw returns and 3-factor Fama and French alphas. I have also tried ranking funds on the correlation between their portfolio weight changes and subsequent stock returns. In all these cases, I find strong evidence of "follow the leader" behavior.

changes in portfolio weights of the followers in the subsequent quarter. This dependence is both statistically and economically significant. Controlling for stock returns and turnover, dollar and share volume that can be attributed to following the leaders ranges from about 15% to 30% of the volume generated by the leaders. These numbers most likely understate the importance of mimicking. As mentioned above, mimicking may occur at frequencies higher than quarterly, which would not be picked up by my estimates. Moreover, market participants other than mutual funds could engage in mimicking as well.

An important complement of these results is the fact that the best funds do not follow the remaining funds. That is, the interaction acts only in one direction. Funds indeed follow the leaders and not just herd into stocks other arbitrarily chosen funds traded in the previous periods.

To further check the robustness of my results, I use leader weight changes to explain the trades of a group of funds certain not to mimic: index funds. As expected, there is no relation between portfolio decisions of the leaders and the subsequent behavior of index funds.

Since leaders by construction hold or have traded in very well performing stocks, funds may appear to mimic the leaders when in fact they pursue positive feedback strategies. However, the "follow the leader" behavior is not explained by trading on stock momentum. As the dependence on best fund trades persists when I control for past stock returns (in both linear and non-linear specifications), this alternative explanation is rejected.

In the second part of the paper, I investigate the characteristics of funds most likely to engage in mimicking and the characteristics of leader trades that elicit the strongest mimicking response. Funds with alphas below the median react to the leader trades about twice as strongly as funds with above-median performance. There is also some (albeit less strong) evidence that small funds and young funds follow the leaders to a greater extent that large and old funds, respectively. As for trade characteristics, trades that are more extreme lead to larger responses than more subdued trades. The "extreme" trades are defined as portfolio initiations and deletions (thus, trades that begin or end at zero weight); these trades also tend to be larger in magnitude. I also show that mimicking is stronger when leaders trade stocks that are less known, or stocks for which informational asymmetries could be more severe. I proxy for these characteristics using the market capitalization, the number of analysts following the given company, and idiosyncratic volatility.

Finally, I investigate whether mimicking makes economic sense. I build portfolios of stocks sorted on the previous quarter leader trades and study their performance. The spread portfolio, long in stocks likely to be bought and short in stocks likely to be sold by the follower funds, yields average returns of about 35 basis points per month in the quarter subsequent to when leaders trade. These returns cannot be explained by the usual factors. The CAPM, the Fama-French, and the 4-factor Carhart alphas are all significant and of economically interesting magnitude of about 35 basis points per month. This abnormal performance is still present when I characteristic-match and control for size and book-to-market. Lastly, characteristic-matched returns indicate that the spread portfolio delivers about 0.16% more per month than a control portfolio matched on size, market-to-book, and past year return. However, the t-statistic on this last abnormal return is only 1.1. While this suggests that the performance of the mimicking strategy is partly driven by momentum, it does not necessarily mean that following the leaders makes no economic sense. To the extent that fund managers are evaluated on the basis of their raw returns or alphas, they can gain a lot from mimicking. Moreover, mimicking can help funds cut research expenses.

The present paper builds on and is related to the vast literature on mutual funds. To the best of my knowledge, the only other attempt to empirically document the "follow the leader" behavior appears in the book by Friend, Blume, and Crockett (1970). Friend et al. study fund holdings for 2 quarters of 1968 and provide some preliminary analysis that supports this hypothesis. However, they do not control for additional explanatory variables, such as individual stock returns, and they do not investigate the determinants of the intensity of mimicking or economic benefits of this behavior.

If many funds follow the leaders, they will likely herd into the same stocks. Thus, the present paper is also related to the literature on herding.[3] It is different, however, in a couple of important points. Firstly, most of the existing papers concentrate on showing that trades across funds are correlated and then look for a potential mechanism that explains this correlation. Since the goal of the present study is to better understand why and how investors trade, I actually begin with such a mechanism and test it empirically. Moreover, the interaction I propose and discuss here has not yet been considered in studies of herding in portfolio decisions. Secondly, the herding literature

[3]Devenow and Welch (1996) review the theoretical literature on herding and the applications in financial economics. Recent empirical papers on herding include Wermers (1999), Welch (2000), Sias, Starks, and Titman (2001), Sias (2004), and Dasgupta, Prat, and Verardo (2005). See also the references therein.

usually investigates if trades are correlated in the given period (say, quarter).[4] This is consistent with funds following each other throughout the quarter, but also with all of them simultaneously responding to a common shock and trading at the same time. On the other hand, "follow the leader" behavior involves cross-autocorrelations: current trades of a group of funds are correlated with future trades of other funds. This distinction is important. For example, most existing studies suggest that herding may be related to the momentum effect of Jegadeesh and Titman (1993). However, if investors herd at the same time their potential price impact will be immediate. For momentum to arise trades need to be spread over time. The evidence presented here indicates that they indeed are.

Cohen, Coval, and Pastor (2005) propose a performance measure based on portfolio comparisons. They find that incorporating similarities in portfolio composition and trades substantially improves the quality of skill estimates. Their evidence gives another reason to try to mimic and become – at least superficially – associated with the best funds. Such associations could directly bring new investment if fund investors use holdings and trades to evaluate skill. Moreover, it could also yield a useful excuse (a "safety net") during bad times. An underperforming manager could defend his portfolio choices by pointing out that while the overall fund returns are low, some of the recent trades are the same as those of the best funds. Finally, investors may benchmark fund performance relative to returns of the leaders. If this is the case, reputational concerns may entice funds to mimic to try to reduce their tracking error relative to the peer benchmark.

In a related study, Frank, Poterba, Shackelford, and Shoven (2004) investigate the feasibility of replicating a funds' portfolio. They show that by investing in the same stocks with a lag, a hypothetical fund can attain returns statistically indistinguishable from its target. However, that paper does not provide evidence that mutual funds – or other investors – indeed engage in this behavior and it does not investigate factors that influence the degree of mimicking.

Finally, there are papers that look at mimicking in other contexts. For instance, Cooper, Day, and Lewis (2001) find "follow the leader" patterns in the way analysts set their earnings forecasts, while Massa, Rehman, and Vermaelen (2005) study the timing of and mimicking in the decision to repurchase stock.

The remainder of the paper is structured as follows. In the next section, I present the data used in this study. Section 2 exhibits and discusses evidence that mutual funds tilt

[4] Froot and Tjornhom (2004) and Sias (2004) are notable exceptions here. Both these papers find evidence that fund trades are cross-autocorrelated.

their portfolios towards stocks previously chosen by the industry leaders and evaluates alternative explanations. Section 3 investigates the relationship between mimicking and the characteristics of the follower funds. In Section 4 I study how the characteristics of leader trades influence subsequent mimicking. Section 5 analyzes the performance of the mimicking strategy. Section 6 concludes.

1 Data description

I combine three data sets in the present paper: the Thompson Financial mutual fund holdings database (formerly known as the CDA Spectrum database), CRSP Survivorship Bias Free Mutual Fund Database, and the monthly CRSP stock database. While merging fund holdings with the CRSP stock data is straightforward using the PERMCO numbers, merging the holdings and the CRSP Mutual Fund database is more troublesome. There is no common fund identifier used in the two data sets. I use the identifier created by Marcin Kacperczyk, who graciously allowed me to use it in this study. This identifier has already been discussed in the literature, for instance in Kacperczyk, Sialm, and Zheng (2005). That paper contains more details on its construction and on merging the two databases.

Since my focus is on actively managed funds, I eliminate index funds from the sample. I begin by searching fund names for the following keywords: “index,” “ind,” “idx,” “market,” and “S&P.” Next, I manually screen funds that came up in the search. I retain funds with names that suggest that the fund follows an “enhanced index” or “managed index” strategy. Managers of funds such as “Nations Fund: Managed Small Cap Index” or “ING Index Plus Protection Fund” are likely to engage in market timing or directly pick stocks and thus should be considered active. In general, in doubtful cases, I assigned funds the active status.

The CRSP mutual fund database includes information about all share classes of a given fund. These share classes correspond to a single portfolio, and are recorded once in the Thompson Financial holdings database. To deal with this discrepancy, for each fund I only choose the share class with the largest number of months with valid returns in the given year. If there are more than one share class that yields the maximum number of months, I follow Cohen, Coval, and Pastor (2005) and choose the one with the lower value of the ICDI fund identifier. Fund performance reported in the CRSP mutual fund database is net of fees and expenses. Since I focus on manager skill, I add expenses back to fund returns.

I adjust stock returns in the CRSP database to reflect the potential effect of delisting. To this end, I use delisting returns whenever they are available from CRSP. If they are not, I follow Shumway's (1997) recommendation and assign the terminal return of -30% to stocks that disappear for performance-related reasons. For some of the tables I also use the number of analysts following the given stock, obtained from the I/B/E/S database. Finally, to measure portfolio performance, I use the Fama and French and momentum factors, downloaded from Ken French's website.

Altogether, my sample covers fund holdings and performance in 96 quarters between the first quarter of 1980 and the fourth quarter of 2003.

2 Do funds follow their industry leaders?

2.1 Definition of leader funds

To choose the leaders I rank funds on their four factor Carhart (1997) alphas and select the top funds. I estimate alphas using two years of monthly return data. For most results presented here, "leader" funds are defined to be those with 4-factor alphas in the top 5% of the current cross-sectional distribution. I have experimented with other percentiles. In particular, choosing top 10% of funds (rather than top 5%) also leads to strong evidence of "follow the leader" behavior in fund portfolio decisions.

As a robustness check, I used other performance measures, such as raw returns and three factor alphas from the Fama and French (1993) model, as well as other estimation horizons (1 and 3 years). Moreover, I experimented with a ranking based on the correlation between portfolio weight changes of the given fund and stock returns in the subsequent quarter. The overall results are similar: for all of these alternative specifications, there is evidence of "follow the leader" behavior.

I also present some results for leaders defined using Honor Roll, the list of the best mutual funds published every year by Forbes. The advantage of this ranking is that it only includes established, well known, and well diversified funds. Moreover, it is likely that Honor Roll funds receive relatively more media exposure than funds sorted on alphas (at the very least, they are prominently featured in Forbes). I show below that for Honor Roll leaders the evidence of following is at least as strong as for funds sorted on alphas.

The leadership definitions I use here do not need to be the perfect measures of fund managers' skill from the point of view of an academic researcher. All that is required here is that funds I label "leaders" are among the most successful ones in the eyes of their peers. Given the importance that standard business education places on alphas, and given that funds with high 4-factor alphas tend to have high raw returns and CAPM or 3-factor alphas,[5] the main measure I use seems well suited here. If managers do not use the 4-factor model for performance evaluation, or if that model is somehow misspecified, one would expect that that would bias this study against finding results. Estimation errors in alphas will likely have the same effect.

The number of funds I assign the leader status to is small. It varies from 13-15 funds at the beginning to about 100 funds at the end of the sample. On average, 35 funds are assigned the best fund status.[6] This is obviously only a small fraction of funds in existence. However, it seems reasonable that the attention of fund managers is focused on relatively few funds that outperform the benchmarks the most. This is exactly what fund investors do. As illustrated by strong convexities in the performance-flow relationship, documented e.g. in Chevalier and Ellison (1997), investors focus their attention disproportionally on a small fraction of the best performing funds. It is plausible that fund managers behave similarly and review the trades of relatively few other funds in their portfolio decisions.

Finally, leaders are chosen without considering investment styles of mutual funds.[7] There are two reasons for disregarding style information. Firstly, the proxy I choose for the actions of leader and follower funds implicitly controls for investment objectives. This proxy is discussed in detail below. Secondly, it is unlikely that funds pick stocks only within their style and would be willing to forgo an attractive trading opportunity only because the stock of interest is incompatible with their investment objective. For example, if a leader fund happens to be a value one, even growth followers may want to incorporate one or two of its stocks into their portfolios. Such additions may be relatively small and the followers would not lose their general tilt towards growth. In fact, Cooper, Gulen, and Rau (2006) show that some funds try to mislead investors by

[5]This evidence is presented in Table I, discussed below.

[6]These numbers correspond to 5% of funds for which alphas could be estimated (thus, funds with valid past returns). Compared to all funds in existence, leaders constitute on average about 3% of the fund universe in any given quarter.

[7]I have estimated the main specifications for same-style leaders and followers for growth and growth and income funds, two categories with the highest number of funds in my sample. The results are similar to those presented here: funds chase the leaders also when leaders are defined within a given style.

changing their investment objectives without changing their portfolios. Thus, one may actually find growth funds that invest in value stocks.

The summary statistics of leader and the remaining funds are presented in Table I. The median leader is larger than the median fund from the other group. The average size, however, is greater for the non-leader funds, which indicates that funds with the highest assets under management rarely appear among the top 5%.

Importantly, leaders are not necessarily smaller than other funds. The measure I use to select leaders, 4-factor alphas, does not seem to favor small or sector funds (that tend to be smaller). This is important, as such funds are likely to be less known and thus may not attract much following.

In terms of performance, leaders truly seem superior. Their average monthly returns are about twice as high as those of the remaining funds. After controlling for three or four factors, the leaders' alphas are about 1.5% per month, while the average alphas of the other funds are essentially zero. Moreover, even though leaders were chosen based on alphas estimated over 2 year periods, their outstanding performance is evident also when one looks at the 1 year or 3 year horizons. It is therefore likely that the managers of leader funds are perceived as attractive mimicking targets.

The third column of Table I provides a glimpse at another subset of the fund universe: 10 funds with the highest 4-factor alphas. The median top 10 fund is larger than the median top 5% fund, which may be a result of the high convexity of performance-flow relationship. The final column of the table corresponds to "above median" funds, or those with alphas between the 50th and the 95th percentile of the cross-sectional distribution. Their average size is much larger than the average size of the "remaining" funds. This is not surprising: one would expect investors to leave the worst funds and move on to the best and, possibly, medium funds.

2.2 Proxy for fund actions

The main hypothesis evaluated in this paper is that portfolio choices of the leader funds are a determinant of other funds' decisions. To test this hypothesis I need to define a proxy that quantifies the interest that leaders and followers exhibit in a given stock. This proxy is the change in portfolio weight a fund allocates to that stock, averaged across all leader (or follower) funds.

Changes in portfolio weights have a number of advantages over possible alternatives.

In particular, they are more informative than measures based on the dollar value of trades or the number of funds trading a stock. The weakness of these two variables is that they are potentially affected by changes in the size of the fund, rather than the fund manager's new information. Since leaders by construction are funds with outstanding recent performance, they will likely experience a net inflow of money. That money will be invested, possibly by just scaling up the fund's current portfolio. In such a case, even if both the number and dollar value of trades are high, they will not carry much new information. An additional problem with proxies based on the number of trades is that they convey intent, but not the magnitude of the leaders' actions. The fact that a few funds are buying the same stock could be less informative than just one fund increasing its allocation by a lot.

For each fund, I use the following formula to compute the change in stock j's portfolio weight between quarters $t-1$ and t:[8]

$$\Delta w_{j,t} = \frac{n_{j,t} P_{j,t}}{\sum_i n_{i,t} P_{i,t}} - \frac{n_{j,t-1} P_{j,t-1}(1+R_{j,t})}{\sum_i n_{i,t-1} P_{i,t-1}(1+R_{i,t})},$$

where $P_{j,t}$ and $R_{j,t}$ are stock j's price at time t and returns between quarter $t-1$ and t, respectively, and $n_{j,t}$ are the fund's holdings of stock j in number of shares. The implicit assumption here is that all trades occur on the last trading day of the quarter. I also account for stocks that funds sell off completely (portfolio weights drop to zero) or introduce into their portfolio (weights increase from zero) by comparing past quarter and current quarter stock holdings.

Changes in weights are computed relative to the weights the fund would have if it did not alter the previous quarter stock holdings. This approach approximates the buy-and-hold strategy. This seems more reasonable that using past quarter weights directly (without accounting for intermediate stock returns), which would impose a negative (positive) bias on stocks that did poorly (well) in the given quarter. The weights and weight changes correspond to mutual funds' stock portfolios. Other assets held by the funds (such as bonds or derivatives) are not considered here as I lack data on their identity and performance.

To get the aggregate measure of the interest leaders (or followers) exhibit in the given stock, I average weight changes across the given subset of funds. I average weight changes for the given stock over only these funds that hold the stock either at the beginning or

[8] For the minority of funds that report their holdings semiannually, I compute weight changes between quarters $t-2$ and t. If the previous report is more than 6 months old, I treat that observation as missing.

at the end of the quarter. Weight changes measured in this fashion are more informative for stocks that are traded only by a few specialized funds. A weight change may be quite large for funds willing to trade the given stock, indicating that these funds are highly interested in it. At the same time, the average over all funds may be minuscule, which would falsely indicate lack of interest. Since every stock is held by potentially a different number of funds, a consequence of averaging across different subsets is that the sum of average weight changes over all stocks may not be equal to zero.

Note that the way I compute weight changes implicitly controls for investment objectives. If a fund is not interested in trading a given stock, it does not influence the average weight change of that stock.

As a robustness check, I reproduced most of the tables using alternative weight specifications (using past quarter weights directly, or normalizing by the total assets of the fund rather than the value of its stock portfolio). The results are very similar to these presented here. I also experimented with other proxies for fund actions. Some of these variables (the weight change in the aggregate leader/ follower portfolio, dollar and share volume generated by the leaders/ followers) are exhibited and discussed below.

2.3 Evidence for following the leaders

Given the leader definition and the proxy for fund actions, I now proceed to test the central hypothesis of the present paper: that funds mimic managers with outstanding past performance. I test for the following mechanism. Leaders trade and, at the end of quarter $t-1$, report their new portfolio composition. This information, together with what these funds disclosed at $t-2$, can be used to infer the trades they executed.[9] Other funds may decide to use that information in their portfolio decisions. Whether they do or do not, their portfolio composition will be reported at the end of quarter t.

I test the mimicking story using the regression framework. The central specification is of the form

$$\Delta w_{j,t}^{follower} = \gamma \Delta w_{j,t-1}^{leader} + \alpha + \sum_{\tau=0}^{T} \beta_{\tau}^{R} R_{j,t-\tau} + \sum_{\tau=0}^{T} \beta_{\tau}^{Trn} Trn_{j,t-\tau} + \epsilon_{j,t},$$

where $\Delta w_{j,t}^{leader}$ is the change in the weight of stock j, averaged over leader funds,

[9]Some trades, most notably round trip transactions that are initiated and closed in the same quarter, would not be recorded in the quarterly reports.

$\Delta w_{j,t}^{follower}$ is change in the weight of stock j, averaged over all remaining funds, and $R_{j,t}$ and $Trn_{j,t}$ are quarter t returns and turnover on stock j. Returns are included in the regression to control for the impact of new information about the stock, while turnover is a catch-all proxy that should capture overall interest in the stock in the given quarter. Individual stock returns should also help control for the impact of positive feedback trading.

For each quarter with valid data, the above specification is estimated on the cross-section of stocks held by mutual funds. These regressions include all stocks for which follower changes can be computed. If leader weight changes are not available for some stocks, I assign the missing leader observations the value of 0. The time series of cross-sectional estimates is then used to compute the final estimates of the regression parameters, as proposed in Fama and MacBeth (1973). I use the Newey-West weighting scheme to obtain standard errors corrected for the potential autocorrelation and heteroskedasticity of the cross-sectional estimates.

The first five columns of Table II summarize the estimates of different variants of the above specification. The "follow the leader" hypothesis is strongly supported. The way mutual funds rebalance their portfolios is significantly related to what leaders did in the previous period. The follower funds move towards stocks whose weights in the leader portfolios increased and away from those whose weights went down.

This effect is statistically strong also when stock returns or turnover are controlled for. Moreover, changes in portfolio weights of mutual funds are strongly positively correlated with recent stock returns. This correlation is not mechanical: as discussed above, weights are computed in a way that adjusts for stock price changes. At the same time, this result is not surprising. Mutual fund preference for well performing stocks has already been documented in the literature (e.g., Grinblatt, Titman, and Wermers, 1995).

Table II exhibits results for only a few of possible return horizons. Most notably, the behavior of the stock in the intermediate quarter (quarter t) is controlled for. As for past performance, different specifications include stock returns over the previous quarter ($t-1$), as well as the previous 2 years ($t-5 \rightarrow t-1$). The last horizon corresponds to the period used for ranking funds on their alphas. I have also experimented with other return and turnover computation periods; the overall results are very similar to these presented here.

The last five regressions in Table II introduce an additional explanatory variable. To explain how the follower funds are changing their portfolios, I add the average follower portfolio weight in stock j, $w^{other}_{j,t-1}$. The specification now is

$$\Delta w^{follower}_{j,t} = \gamma \Delta w^{leader}_{j,t-1} + \delta w^{follower}_{j,t-1} + \alpha + \sum_{\tau=0}^{T} \beta^R_\tau R_{j,t-\tau} + \sum_{\tau=0}^{T} \beta^{Trn}_\tau Trn_{j,t-\tau} + \epsilon_{j,t}.$$

There is a very strong negative relationship between weight changes and the average portfolio weight the follower funds had in the previous quarter. Conditional on having a sizable position in a stock, funds are more likely to sell and decrease their portfolio weight. Moreover, I have re-estimated Table II specifications using another explanatory variable: the weight changes averaged over the follower funds in the previous quarter (i.e., one quarter lag of the dependent variable). The results are very similar to those obtained for average weights. Thus, there is a strong negative correlation between weight changes and both lagged portfolio weights and lagged weight changes averaged across the given group of funds (leaders, followers).

A possible explanation of this phenomenon is the high portfolio turnover of mutual funds. To produce turnover as high as that observed in the data (the average annual turnover exceeds 100%), funds could not maintain large positions for a long period of time. Another possible explanation are errors in the holdings database. Consider a fund that maintains a constant weight of 10% in a stock. Suppose that due to an error in the database, the recorded portfolio weight jumps to 50% in the given quarter. I assign a weight change of +40% to this quarter and -40% to the next one (when the weight is again correctly recorded as 10%). The effect is the negative autocorrelation in portfolio weights. The abundance of measurement errors is one of the unfortunate features of the CDA/ Spectrum database and is widely known (e.g., it is discussed in WRDS documents pertaining to the database). While I do my best to clean the data (by comparing the size of the fund to the market capitalization of its recorded portfolio or by eliminating extreme weight changes), it is unlikely that I was able to eliminate all errors. As I focus on cross-correlations between weight changes of different sets of funds, it is unlikely that such errors drive my main results.

Table III inverts the specifications and relates leader weight changes to lagged weight changes of the followers. Such regressions constitute an important test of the "follow the leaders" hypothesis. If I find that leaders themselves mimic other funds, then a different explanation of the phenomenon will be required. To see if that is the case, I first regress leader weight changes on the lagged weight changes of the remaining funds. The results, summarized in the first five columns of Table III, indicate that there is little evidence of leaders mimicking the followers. The follower variable is in all cases insignificant; in fact, in a couple of specifications it is negative. In the last five columns of Table III, the explanatory variable is the lagged weight change of the worst funds (with alphas below the median). In all specifications, the follower coefficient is negative and insignificant.

Another way of testing whether the phenomenon described here is indeed mimicking involves index funds. Given their investment philosophy, index funds are certain not to engage in "follow the leader" behavior. To check if that is indeed the case, I have reproduced Table II using weight changes averaged over index funds. The leader coefficients for index funds are always insignificant with t-statistics that never exceed 0.6 in absolute value. Moreover, depending on specification, estimates change sign from positive to negative. These findings are reassuring and suggest that my findings are not mechanical.

While past actions of the leaders have a strong statistical relationship with the subsequent portfolio choices of the follower funds, the coefficients presented in Table II are tiny. When the best funds increase their weights in the given stock by 1%, the average weight of the follower funds increases only by 0.011% to 0.016% (or 1.1 to 1.6 basis points). Are these numbers large enough for the mechanism I describe here to be economically important? Based on Table II alone, it is difficult to answer this question. The dependent variable are weight changes averaged over all follower funds. The number and size of the followers are potentially quite large. It is possible that even the low estimates from Table II correspond to a substantial flow of money. Table IV investigates if it is the case. The specifications in Table IV use variables other than average changes in portfolio weights. In its two first columns, the dependent variable is the weight change in the aggregate portfolio of follower funds (rather than the average weight change computed across all followers). The main independent variable in that case is the lagged weight change in the aggregate portfolio of the leaders.

The "follow the leader" hypothesis is supported also at the aggregate level. Changes in the aggregate leader portfolio weights are significant and their estimates are similar in magnitude to those reported in Table II. Whenever the weight on a stock in the aggregate leader portfolio increases by 1%, in the subsequent quarter that stock's weight in the aggregate portfolio of the followers increases by about 1 basis point. In terms of the money invested by the follower funds, their response is about one third of the investments by the leaders. This is because the size of the aggregate follower fund portfolio is about thirty times larger than the aggregate best fund portfolio.

It is interesting that the lagged coefficient on the weight of the aggregate follower portfolio is still significantly negative. That is, if follower funds as a group are holding a sizable position of a given security, they are likely to decrease its portfolio weight in the future. However, the magnitude of this variable is more than 10 times smaller than the corresponding estimate from Table II. Thus, this motive for rebalancing is of less importance in the aggregate portfolio than in the portfolios of individual funds.

The next three columns of Table IV relate the aggregate dollar volume generated by the leaders to the aggregate dollar volume generated by the remaining funds. The univariate regression implies that close to 30% of the follower dollar volume can be attributed to mimicking the leaders. When stock returns are controlled for, that fraction decreases to about 20%. The last specification in this group uses log of dollar volume. Also in that case the leader variable is highly statistically significant, although given the log transformation, the economic magnitude of the point estimates cannot be readily gauged.

The final group of regressions in Table IV employs share volume to measure actions of leaders and followers. As may be expected from earlier specifications, leader share volume is an important predictor of how much the follower subsequently trade. According to this measure, about 16% of leader volume is subsequently reproduced by the followers.

The estimates from Table IV suggest that for every dollar leaders invest in a stock (and for every 10 shares they buy), the follower funds additionally invest about 15 to 30 cents in that stock (or buy additional 2 shares). Such magnitudes imply that "following the leader" behavior is indeed important economically, even though the estimates in Table II are small. In fact, it could be argued that since the weight changes of the followers are averaged over so many funds, the coefficients should be relatively small. They would only be large if the follower funds mimicked en bloc or if a few funds ventured sizable fractions of their portfolio. It is unlikely that mimicking at such a scale could be sustained, given that it would give leader funds strong incentives for strategic behavior, lead to severe temporary liquidity pressures, etc. For mimicking to be sustained in equilibrium, it needs to be somewhat moderate and perhaps limited only to a few follower funds.

The economic significance of mimicking, quantified in Table IV, is most likely understated. Firstly, if mutual funds engage in this activity, there are probably other market participants who also try to follow the leader funds. Secondly, there are other, possibly more timely sources of information about fund portfolios than quarterly reports that I use in this study. Such sources may include media interviews, data funds voluntarily disclose on their websites, or information exchanged in informal networks of fund managers. These other sources of portfolio information could be potentially quite important because leaders have an incentive to make their stock picks known as soon as they finalize their trades. Once they obtain the desired position, potential mimicking could lead to a price increase and improve their returns. Thus, mimicking could be possible also before the quarterly reports are released. However, even though some funds may be able to mimic already in the quarter when the leaders trade, I will not pick up their activity in my regressions. This may lead to a substantial downward bias in the estimated magnitude of mimicking. When weight changes are regressed on the same quarter leader weight changes, the leader estimates are 5 to 10 times larger than those reported in Table II. Unfortunately, in that case, it is impossible to differentiate mimicking from a simultaneous reaction of all funds the same new information. For this reason, I have decided against reporting the results for the contemporaneous portfolio weight correlations.

Table II regressions all have very small coefficients of determination. Even in the most comprehensive specifications R^2s are only about 4%. To some extent, this is to be expected from regressions that try to explain trades in a large universe of stocks (each regression in Table II includes on average more than 4000 stocks) using only a handful of explanatory variables. In particular, I do not control for a multitude of stock-specific events, such as earnings announcements or news about product innovations. This is because this paper is not an attempt to build a model that explains why and how funds trade with the highest possible R^2. My goal here is more modest: to show that in their portfolio choices mutual funds take account of what other funds are doing.

The low R^2s indicate that there are many other variables that influence portfolio decisions. In the worst case, leaders' actions appear significant only because they are correlated with an important omitted variable. While it is impossible to prove that this is not the case, it is difficult to propose a suitable candidate for the omitted quantity. Such a variable would need to be better proxied for by changes in leaders' weights than by stock returns or turnover. Moreover, it would need to be correlated with what leaders did one quarter prior to when other funds trade, but not correlated with what other funds did at that time.

Altogether, the results discussed so far support the hypothesis that mutual funds are following their industry leaders. An alternative explanation that may generate similar empirical patterns involves positive feedback (momentum) trading. As documented e.g.

in Grinblatt, Titman, Wermers (1995), funds tend to chase stocks with high recent returns. Leaders are selected on their performance, so by construction, the stocks they bought recently have had to deliver high returns as well. It is possible that other funds subsequently buy the same stocks not because they are following the leaders, but merely because they pursue momentum strategies.

This alternative explanation is unlikely to hold. In most specifications in Table II, I control for stock returns, both in the quarter in which followers rebalance and in the previous quarters. Even though leader coefficients drop somewhat in magnitude when past stock performance is controlled for, they still have significant impact. A potential problem here is that returns only enter in a linear fashion, and changes in leader weights could proxy for nonlinearities. For instance, funds could focus mainly on stocks that did particularly well in the recent few months. Such a convexity in stock performance-fund reaction relationship may be better proxied for by leader weight changes than by stock returns. Table V investigates if that is the case.

Regressions in Table V incorporate non-linearities into fund reaction to stock returns in the quarter the best funds traded (quarter $t-1$, the first three columns) and in the previous 2 years (quarters $t-5$ through $t-1$, the last three columns). For each of these horizons, the first two regressions add quadratic and third order terms of returns. The last regression uses a dummy variables that takes the value of one for stocks that did particularly well (top 5% of the cross-sectional distribution). If nonlinearities are indeed a problem here, these additions should eliminate the impact of the leader funds. They do not. Leader coefficients are similar to those exhibited in Table II both in terms of their magnitude and statistical significance.

Interestingly, the coefficients on the higher order terms and on the dummy variables are all negative and – at least for quarter $t-1$ returns – significant. Possibly, the relationship between returns and weight changes is in fact concave. This may be because stocks with the best performance experienced returns that are overwhelmingly larger than that of other stocks. The average quarterly return of a stock in the top 5% of the performance ranking is 80.4%. In some sense, returns of this magnitude correspond to outlying observations. It is possible that the linear relationship of Table II overestimated the weight changes for the very best performing stocks. Once the relationship is allowed to be non-linear, the extra explanatory variables in Table V yield negative estimates. This inference is supported by changes in the return coefficients (the linear terms). Once higher order terms are controlled for, estimates from Table V are all higher than the corresponding estimates from Table II, which again points towards concavity.

To further test whether my results are driven by positive feedback strategies, I re-estimated the main specifications from Tables II and V only for stocks that did not have extreme performance. I have restricted the sample to stocks with 1, 2, or 4 quarter returns between 25th and 75th percentile of the cross-sectional distribution, as well as stocks below the cross-sectional median. I find strong evidence of the "follow the leader" behavior also for these subsets of stocks.

The results discussed above hinge on the identification of funds that are attractive mimicking targets. A drawback of defining leaders using returns or alphas is that leaders could sometimes be relatively unknown or young and small funds.[10] Only some of the funds labelled "leaders" in the analysis above may be important or visible enough to attract a following. This misspecification of the leader status will likely work against finding any results and, from this point of view, the estimates are probably biased downwards.

To complement the findings for funds sorted on their 4-factor alphas, I employ another definition the leaders, based on the Honor Roll of funds that Forbes magazine publishes every year. Forbes requires funds on the ranking to be well established and have experienced managers. Moreover, only well-diversified funds can make it to the Honor Roll – all sector funds are excluded. Forbes typically publishes the Honor Roll in the summer. I define leaders as funds that make the grade in the given year[11] and estimate the main specifications from the previous tables. The results are summarized in Table VI.

The estimates in Table VI indicate that the impact of leader trades is positive and significant. Moreover, point estimates are about 50% larger than those reported in Table II. The mimicking effect is stronger for Honor Roll leaders than when leaders are based on alphas. Possibly, some funds with high alphas may not in fact be attractive mimicking targets and the Forbes ranking may be a cleaner measure of the leadership status. Another explanation is that given the increased media exposure of the Honor Roll funds, it may be easier to learn what their current portfolios look like (e.g., from interviews that these fund managers give).

Interestingly, while turnover is not an explicit criterion in the Honor Roll selection, one of the characteristics of the Honor Roll funds is that they have, on average, very low

[10]Since I use alphas estimated over two years of past data, the youngest funds are never among the leaders. Moreover, as Table I shows, leaders defined on alphas are not necessarily smaller than other funds.

[11]I also experimented with funds on the Honor Roll in the given and the previous, or the given and the next year. The results are similar.

turnover of 61%. In comparison, the average fund has turnover in excess of 100%. By this metric, leaders trade only about half as often as the average mutual fund. This means that it may be easier to follow an Honor Roll fund based on the portfolio disclosures. Since these funds trade relatively rarely, their past holdings are a less noisy signal of what the current portfolio of the leaders looks like. Thus, a part of the increase in the mimicking intensity from Table II to Table VI can perhaps be attributed to the low turnover of Honor Roll funds.

2.4 Following the leaders or slow diffusion of information?

While the patterns in the data are consistent with following the leaders, there is also another explanation. It is possible that funds do not directly observe each other's portfolios, but instead receive correlated private signals at different points in time. If, for some reason, the leader funds consistently obtain new information earlier than other funds, then the patterns presented in Tables II-VI could arise even if there is no conscious mimicking.

To test one hypothesis against the other I divide stocks into two groups: one with recent information events and one without them. Under the mimicking story, the effect should be visible in both subsets. Under the alternative, it should be limited to (or at least stronger in) for stocks that experienced news events: slow diffusion of information could only be a factor when there is new information. The proxy for news events I choose here is based on analyst forecasts of EPS for the given fiscal year. I compute the changes in the median EPS forecast over the two quarters in which the leaders and the followers trade. The absolute value of the change should capture the amount of news pertaining to the given stock. This proxy is far from perfect. Ideally, I would like a measure of information that is idiosyncratic to the given company. News about EPS, however, may contain common factors, for example shocks to oil prices.

I divide stocks into two groups: these with the absolute value of the forecast change higher than or equal to the median ("news stocks") and with the absolute change below the median ("no news stocks"). I then estimate the mimicking regressions separately for these subsets and use the time series of cross-sectional estimates to evaluate the mean difference between the mimicking coefficients of news and no news stocks. The results are summarized in Table VII.

The main message of Table VII is that the follow the leader effect is strong in both subsets of stocks. The mimicking coefficients are positive and significant in all specifications. However, the estimates are smaller than those reported in Table II. As I show in Section 4 below, the mimicking effect is much stronger for stocks that are poorly covered by analysts, including stocks with no I/B/E/S analyst data. There are more than 1000 of such stocks in the average quarter and they do not enter the regressions in Table VII. Since the stocks where mimicking is the strongest are eliminated, the magnitude of the effect is smaller than in the full sample.

To compare the two sets of estimates (for "news" and "no news" stocks) I use the Fama-MacBeth (1973) methodology. From the cross-sectional regression estimates, I build the time-series of the differences of the coefficients and use it to estimate the average difference and its t-statistic. The results of this test are summarized in the bottom panel of Table VII. Although the point estimates of stocks with little new information are smaller than those of stocks with much new information, the difference between the two is insignificant.

To check the robustness of this result, I have also experimented with different breakpoints for "news" and "no news" stocks. For instance, when "no news" stocks are those with the absolute forecast change below the 30th percentile, the Δw_{t-1}^{leader} coefficients for the three regressions reported in Table VII are 0.009, 0.009, and 0.01 with t-statistics of 2.148, 2.252, and 2.475, respectively, so there is evidence of mimicking also for these stocks. The differences between news and no-news stocks are larger than the ones from the table: 0.003, 0.003, and 0.002, but still insignificant (their respective t-statistics are 0.701, 0.707, and 0.426).

Thus, there is little evidence that the effect is limited only to stocks with recent news events. However, the change in the EPS forecast is an imperfect proxy for new information, so it is difficult to treat this test as decisive.

Another way to test the follow the leader hypothesis against slow information diffusion is to take advantage of the differences in the frequency with which leaders disclose their portfolio holdings. Although for the most part of my sample period the SEC-mandated frequency was semi-annual, the majority of funds submitted their portfolio reports every quarter. However, in most quarters (83 out of 96 sample quarters) there is at least one leader fund for which the previous report is 6 months old.[12] This enables me to compare the impact of frequently-reporting leaders to that of those that only report every 6 months.

If the patters I uncovered are driven by slow diffusion of information, the influence of

[12] If the previous report is older than 6 months, I do not use this report and treat the data as missing.

infrequent reporters should be smaller. When portfolio decisions are revealed only every 6 months, there is, on average, more time for private information of the leaders to diffuse to the follower funds. Followers will possibly react earlier, even before the leaders will reveal their new portfolios, and the cross-correlations between weight changes should disappear or at least decrease. On the other hand, if funds indeed mimic the leaders, even infrequent reports could be perceived as valuable. In the extreme version of this story, information reaches the followers only via portfolio disclosures and their impact should be irrelevant of the reporting frequency.

To test the above hypothesis, I compute weight changes separately for frequently- and infrequently reporting leader funds. I then estimate the benchmark regressions using these two different variables. When Δw^{leader} is computed only for funds reporting in every quarter, the results are very similar to those presented in the paper: there is a pronounced effect of the leader funds. When Δw^{leader} is computed for the infrequent-reporters, its estimate is still positive, but considerably lower and insignificant, for example:

$$\begin{aligned}
\Delta w_{j,t}^{follower} \quad = \quad & 6.968 \; + \; 0.005 \Delta w_{j,t-1}^{leader} - 0.104 w_{j,t-1}^{follower} + 0.096 R_{j,t} + 0.071 R_{j,t-1} \\
& (9.235) \;\; (0.981) \qquad\quad (-11.390) \qquad\qquad (5.722) \qquad (4.943) \\
& +0.115 Trn_{j,t} - 0.256 Trn_{j,t-1} + \epsilon_{j,t} \\
& \;\; (0.836) \qquad (-1.858)
\end{aligned}$$

where t-statistics are reported in parentheses.

The estimates of Δw^{leader} coefficients are statistically indistinguishable from zero. This may be interpreted in favor of the slow diffusion of information: there is little evidence that funds pay attention to infrequently reporting leaders. On the other hand, since there is a longer lag between disclosures of infrequent reporters, it is more likely that followers learn about the leader trades from other sources (e.g., media interviews). Thus, infrequent reports could be relatively less important also under the "follow the leader" story.

The fact that the mimicking estimates are smaller and insignificant for infrequent reporters can be also explained differently. A possible reason for the large standard errors is that there are very few leaders with semiannual – rather than quarterly – reports. Even though in 83 out of 96 sample quarters there is at least one such leader, in many of these quarters Δw^{leader} is based on trades of only one or two leader funds and is perhaps less informative. Also, since there are fewer leader funds, the set of stocks with non-zero leader weight changes decreases by about 40% (it drops from the average of 1178 per quarter to 704 per quarter). In regressions reported in the previous tables, I set the leader weight change equal to zero for stocks the leaders did not trade in. Interestingly, when I estimate the regressions only for stocks the leaders traded in, the standard errors grow smaller while the point estimates slightly increase to about 0.05-0.08. Consequently, the t-statistics increase from about 0.3-1 to about 0.6-1.8.

3 Which funds follow industry leaders?

In this section I investigate which funds are more likely to follow the leaders. Such an analysis could shed light on possible reason why funds mimic. There are two broad explanations why the follow the leader effect may arise.

Firstly, mimicking may occur when leaders are perceived as funds with superior information or skill. Following them is then an attempt to free-ride on this advantage. A side benefit of doing so is a decrease in research expenses (arguably, following the leaders is cheaper than independent stock analysis).

Secondly, following the leaders may be driven by reputational concerns. A fund's reputation may improve if that fund's portfolio is similar to portfolios of the best funds, or if that fund engages in the same trades as the industry leaders. This situation could arise if investors gauge fund managers' skill by comparing the compositions of fund portfolios. Such a measure was proposed in Cohen, Coval, and Pastor (2005), who show that it does better than raw returns or alphas. Copying leaders' portfolio decisions is a simple way of improving a fund's holdings-based measures and consequently its reputation as well. Reputation may be also related to career concerns, as pointed out in Chevalier and Ellison (1999). Fund managers with the lowest reputation are most likely to lose employment or be downgraded to a smaller fund (and hence smaller salary). Such managers may be enticed to try to improve their reputation even at the cost of a potentially sub-optimal portfolio strategy. In particular, they may mimic the decisions of the industry leaders to share the glory (or, perhaps, share the blame) with the best of the lot. Finally, mimicking will likely decrease funds' tracking errors with respect to their more successful peers, which may also contribute to their reputation.

In Table VIII I evaluate the differences in mimicking displayed by funds sorted on their past performance, size, and age. All these variables are likely to be correlated with fund reputation and can help test for the importance of reputational reasons for mimicking.

The first two columns of Table VIII contrast funds with 4-factor alphas below the median and funds with above median performance (alphas above the median, but below the top 5%). The hypothesis investigated here is that the worst funds mimic more than the above-median funds. Managers of funds with low performance obviously rank poorly on return-based measures. It may be relatively more important for them to provide non-return evidence that they are doing a good job. Proving that their portfolios are similar to those of the industry leaders may superficially constitute such evidence. On the other hand, funds near the best performers may have lower incentives to engage in mimicking. Such funds are not at the top of ranking lists, but they are still better than average. Their managers may not feel as pressured to prove their worth. In fact, the tournament literature (e.g., Brown, Harlow, and Starks, 1996) indicates that it may be in their interest to pursue trades orthogonal to those of the leaders. Mimicking may take them closer to the leaders but is unlikely to advance them to the highest tiers. Pursuing different (possibly riskier) strategies may increase their chances of overtaking the current leaders.

While the specifications estimated in Table VIII are similar to those in Table II, the dependent variable is computed differently. In Table II it was the weight change averaged over all non-leader funds. Now, in the first (second) column of Table VIII, weight changes are averaged only across the below median (above median) funds.

While leader coefficients are positive and statistically significant for both the worst and the above median funds, they are much higher for below median funds. I compare the differences between well and poorly performing funds using the same approach as in Table VII and report the results in the bottom panel of Table VIII. The difference between the leader coefficients is significant, with t-statistic of about 2.1.[13] Thus, above median funds mimic appear to have less incentives to follow the leaders than funds at the bottom of the performance distribution. While the differences in incentives may be related to the strength of reputational concerns, they may be caused by informational issues as well. Managers of funds with the worst performance will not only have lower reputation, but also lower assessment of their own skill levels. Thus, they may be more eager to mimic other funds simply because they have more to gain from free-riding on

[13]The difference is also significant for other specifications. Here, I only report detailed results for one of them.

the skill of managers with (seemingly) higher ability.

The second fund characteristic I consider here is size. In the third and fourth column of Table VIII the weight changes are averaged over small (bottom 20%) and large (top 20%) funds. The key explanatory variable, as before, are lagged weight changes averaged across the leader funds. For both groups of funds the coefficient on the leader variable is positive and significant. Moreover, small funds seem to mimic more than large ones. However, the difference between the leader coefficients obtained for these two sets of funds is not significant.

Finally, in the last two columns of Table VIII, I compare young and old funds in a similar fashion. Young (old) funds are those whose age, inferred from the CRSP mutual fund database[14] does not exceed 3 years (is at least 10 years). Both groups of followers tend to mimic: the leader coefficients are both positive and statistically significant. While the estimate for young funds is much higher than that for old ones, the difference is not, however, statistically significant. The t-statistic, exhibited in the bottom panel, is only 1.1.

Both fund age and fund size are likely to be correlated with reputation. Funds grow in size primarily because people who trust them with their money have high opinion (or at least hope) of the fund manager. Similarly, funds survive to an old age and avoid liquidation or acquisition by another fund if their performance and brand name, and hence reputation, are strong enough. From this point of view, the evidence from Table VIII is in line with mimicking for reputational reasons. However, for both fund size and age, differences in the leader coefficients are insignificant, so the evidence does not unambiguously favor reputation-based mimicking.

4 Which trades are likely to be followed?

While the previous section investigates follower characteristics, the present one focuses on leaders' trades. This analysis could contribute to understanding funds' motivation to mimic, at least under the information-related mechanism. If funds believe that leaders have an informational advantage or superior stock-picking skills, they will mimic to try to free-ride on that advantage. The extent of mimicking should then be related to the incremental informativeness of the best funds' trades. I test this hypothesis below using

[14]The database records years in which funds were organized. If different share classes of a fund were organized in different years, I select the earliest date (i.e., the one that gives higher fund age).

a variety of proxies for the informativeness of the trade.

Firstly, it seems reasonable that more extreme portfolio decisions (such as an addition of a new stock into or an elimination of a stock from the portfolio) carry more information than more subdued moves (such as an adjustment, but not outright deletion, of an existing position). It turns out that such extreme trades also tend to be larger. While the average weight changes for the two categories of trades are similar (about 0), the initiations and deletions have much greater standard deviation (1.8% versus 0.8%). Moreover, the range of the middle 90% of the initiations and deletions is from -2.6% to 2.9%, while the corresponding numbers for other trades are -1.2% and 0.9%.

Table IX tests if extreme trades indeed lead to more mimicking. In its first three columns, I estimate the mimicking regressions using only a subset of trades in which leaders deleted a stock from or introduced it into their portfolios. That is, to compute weight changes between $t-1$ and t, I only use stocks that leaders had in their portfolios at time $t-1$ but not at t, or at time t but not at $t-1$. The leader variable in the remaining three columns is based only on trades that begin and end at non-zero positions. Thus, in both cases, the main explanatory variable is different from the one used in Table II, where averages were taken over all trades. As before, the dependent variable are weight changes averaged over all remaining (non-leader) funds. That second average includes all follower weight changes of the given stock (not only those from or to zero).

The results from Table IX are in line with the informational explanation. Leader coefficients are much higher for initiations and deletions, in the first three columns of the table. The coefficients on non-initiations are smaller in magnitude and they are all insignificant. Moreover, when past portfolio weights are controlled for, the estimates of Δw^{leader} corresponding to non-initiations turn negative (they are about -0.001, or -0.1 basis points per 1% weight change in the best fund portfolios); they remain insignificant. The bottom panel of the table indicates that the differences between extreme and other trades are in all cases positive, and, as long as past portfolio weights are controlled for, these differences are significant.

These results are not driven by stocks that just appeared or were eliminated from the exchange. Some specifications from Table IX include returns in the quarter after leaders trade, so portfolio deletions are not driven by bankruptcies, unless of course leaders can predict which stocks will go bankrupt in the near future. Similarly, the effect still persists when I control for past returns, so initiations are not stocks that had IPOs in the quarter when leaders trade.

Other proxies for trade informativeness are related to characteristics of the traded stock. The fact that a fund purchases $1 million worth of IBM may not be as informative as a purchase of $1 million of a relatively unknown stock. The second trade likely coneys more information than the first one and should lead to a larger reaction. I test this conjecture in Table X by adding an interaction between leader weight changes and a proxy for asymmetries in information about the traded stock.

In the first three columns of Table X the proxy for a company's opaqueness is the log of its market capitalization in thousands of dollars. The interaction of that variable with leader weight changes yields negative coefficients. Moreover, the estimates are significant whenever past portfolio weights are controlled for. Thus, when leaders trade in smaller stocks, the follower reaction is more pronounced. Notice that compared to the previous tables, the magnitude of Δw^{leader} coefficients is much higher when the interaction variable is included. For example, Table II estimates are as much as five times lower, which may suggest that Table X implies a much increased intensity of mimicking. Such an inference, however, would be misleading. Consider a tiny stock, perhaps with the market capitalization of $10 million. The leader coefficient for that stock will be about 0.022: the point estimate of about 0.05 needs to be corrected for the interaction term of $-0.003 * \log(10000)$. Thus, even for very small stocks the leader coefficients are much smaller than 0.05.

The middle three columns of Table X use a different proxy: the log of the number of analysts plus 1. Analyst coverage is related to the visibility of the stock and also to the severity of information asymmetries about the company. If investors considered well informed trade a stock with few analysts, their actions may lead other investors to substantially revise their beliefs about that company. If this is the case, the interaction coefficients should have negative signs. Table X documents that they indeed do. The interaction terms are significant and imply a higher degree of mimicking for stocks with low analyst coverage. For instance, Δw^{leader} coefficients for a stocks followed by a single analyst are about 0.021. When a stock is widely followed, these numbers dramatically drop in magnitude. A stock followed by 20 analysts would only command a coefficient of about 0.002.

The last three columns of Table X interact leader weight changes with idiosyncratic volatility of the stock that leaders trade. The interaction terms consistently earns a positive and significant estimate. This again supports the hypothesis that mimicking is stronger whenever leaders trade stocks that are relatively opaque. When the idiosyncratic volatility is used, the estimates of the leader variable alone become insignificant.

This occurs because all stocks have non-zero idiosyncratic volatility. The leader variable is still significant, but this time is affects the results through the average idiosyncratic volatility in the interaction term. When I reestimate the regressions by interacting weight changes with demeaned log-volatility, the coefficient on weight changes is positive and significant.

The results from Tables IX and X lend support to the hypothesis that more informative trades elicit a larger mimicking response. This finding is to some extent surprising. Small stocks or stocks with few analysts following them are typically less liquid than other stocks, so following the leaders into such stocks is more difficult. The fact that in spite of their low liquidity, trades in such stocks are mimicked more constitutes additional evidence that mimicking is driven by informational concerns.

5 Performance of mimicking-based portfolio strategies

The previous sections provides evidence that managers pay attention to what the leader funds do and use that information in their portfolio decisions. In this section, I investigate if this behavior makes economic sense. Is following the leaders more reasonable than, say, passively investing in the benchmarks?

A related issue is the potential price impact of the trades of mimicking funds. They may have some – potentially short lived – effect on prices. The lead-lag relationship between the trades of the leader and the follower funds can empirically look very similar to information diffusing slowly from the best to the other funds. As illustrated in the model of Hong and Stein (1999), such a phenomenon may have price impact and bring about return momentum.

Finally, performance analysis may contribute to the reputation versus information tests from the previous sections. If mimicking is driven by new information inferred from the best fund trades, that information should be impounded in stock prices. Leaders alone may not invest enough to move prices to the value implied by their information because of their limited size and concerns that a large position would lower their diversification. On the other hand, reputation-based mimicking should have no price impact, or, at most, short lived liquidity-related effect and a subsequent reversal.

To investigate these issues, I construct a portfolio strategy based on the leaders' trades and study its performance. At the end of each quarter, stocks are ranked on Δw^{leader}. Five value-weighted portfolios are then created based on this sort. These portfolios are held for three months, until the next reporting date. The extreme portfolios contain stocks in which the remaining (non-leader) funds are likely to trade.

The first panel of Table XI presents the average leader weight changes per portfolio. The two extreme quintiles correspond to average changes of about -1.3% and 1.4%. Given that the average leader has assets well in excess of $300 million, such re-allocations correspond to sizable investments. The relatively high standard deviations suggest that weight adjustments larger than 1-1.5% are not exceptional.

The performance of the five portfolios is summarized in the second panel of the table. The returns on the fifth portfolio (corresponding to the highest weight changes) are the highest. That portfolio also boasts statistically significant CAPM and 3-factor alphas of about 25 to 35 basis points per month. Its 4-factor alpha is about 22 basis points and not statistically significant with a t-statistic of 1.86. The first portfolio (corresponding to the lowest weight changes) yields average returns that are substantially lower than those of the fifth one. However, they do not seem to be abnormally low as the alphas, while negative, are all insignificant. To some extent, this is to be expected. Price impact (if any) should be more apparent in the buy portfolio (portfolio 5) than in the sell portfolio (portfolio 1). Firstly, it is much easier to buy a stock than to short it, and outright sale is only possible if the mutual fund (or some other market participant) has the given stock in their portfolio to begin with. Secondly, the leader funds are likely to repeat their purchases of the stocks. Given their superior performance, these funds attract new investment. They will likely invest some of the new money into the same stocks they held at the end of the previous quarter. This will create additional price pressure above that caused by the follower funds and could help move prices.

The last column of Table XI presents the performance of the 5-1 spread portfolio that goes long in stocks with the highest and short in stocks with the lowest leader weight changes. This zero-investment portfolio earns average returns of 0.35% per month with a relatively low standard deviation of 2.3% per month. For comparison, the standard deviations of the five base portfolios are all about twice as high, while in my sample period (1980 to 2003) the standard deviations of factors HML and UMD are 3.2% and 4.4%, respectively. The low standard deviation of the spread portfolio arises because factor loadings of portfolios 1 and 5 are fairly similar. The spread portfolio is then approximately factor-neutral. Because of that, returns on the spread portfolio are not be due to exposures to the usual risk factors. All of the CAPM, 3-factor, and 4-factor alphas of the spread portfolio are positive and statistically and economically significant at about 35 basis points per month.

By construction, stocks traded by leaders experienced exceptional past performance – they are responsible for the outstanding alphas of these funds. Hence, some of the performance of the five portfolios may be attributable to momentum. Despite its momentum factor, the 4-factor Carthart model is known to poorly describe returns of individual stocks sorted on their past performance. For this reason, I also compute characteristics-matched returns. To each stock in the five portfolios I assign a control equally-weighted portfolio of stocks that are in the same decile of the characteristic of interest. If a stock cannot be matched (perhaps because it does not have a valid market-to-book or past year return) I drop that stock from the analysis.

The bottom panel of Table XI reports the differences between returns on the portfolios and those of a characteristics matched benchmark. When the characteristics matched include size and past year performance or size and market-to-book ratios, the abnormal return on the spread portfolio is still positive and statistically significant. When all three characteristics are matched, the abnormal performance of the both the fifth and the spread portfolio is still positive and of economically interesting magnitude of about 15 basis points per month. However, both these figures are insignificant. Their t-statistics are only 1.5 and 1.1, respectively. Thus, even though the average characteristics-matched returns point in the same direction as alphas, they do not yield unambiguous conclusions.

A troubling founding of Table XI is the behavior of the fourth portfolio. Although its alphas are insignificantly different from zero, its average raw return is the lowest across all five portfolios. That is surprising, as the average Δw^{leader} for this portfolio is larger than zero. As Table IX shows, however, most of the mimicking activity arises in response to more extreme portfolio adjustments, such as initiations or deletions. It is possible that the weight changes in the fourth portfolio are simply too low to attract other funds. If that is the case, than the lack of abnormal performance should not be surprising.

Following the leaders yields sizable rewards, at least in terms of the covariance-based asset pricing models. Funds that mimic seem to be able to generate substantial alphas. Another explanation of the patterns in Table XI, however, is that the abnormal returns are caused by the mimicking to begin with. As funds invest in the stocks previously traded by leaders, they move their prices because of temporary liquidity shortages. If this is the case, one would expect price reversal in the longer term.

Figure 1 describes the long-term performance of the spread portfolio. It exhibits monthly 4-factor alphas of the portfolio, as a function of time elapsed since the information about leaders' trades was released. The alphas correspond to the following strategy. At the end of the quarter in which leaders trade, the composition of the five portfolios is recorded. After a waiting period of 0 to 15 quarters, these portfolios are created and held for a quarter. At the end of that quarter, portfolios are rebalanced. The alphas of these portfolios, as a function of the length of the waiting period, are exhibited in the graph. Its first point, corresponding to the waiting period of 0, is the alpha from Table XI. The next one is the monthly alpha of the strategy that records the leader weights at the end of quarter t and invests in the spread portfolio at the beginning of the quarter $t+1$ (thus, after waiting for a quarter). The dotted lines indicate pointwise 95% confidence intervals for the alphas.

Figure 1 indicates that there is little evidence that the abnormal performance of the first quarter reverses. Alphas other than the first one oscillate around zero. The only other estimate that is statistically significant corresponds to skipping 42 months and yields the alpha of -0.30 with a t-statistic of -1.989. The only pattern suggestive of a price reversal is the string of three negative alphas at months 36, 39, and 42. Thus, there may be a possible price decline around 3 years after the information about the leader portfolio choices are released. Such a late reversal is difficult to reconcile with liquidity pressures. In the absence of new information, prices should probably revert earlier. Moreover, the downward trend seems to be an artifact of the four factor model of Carhart (1997). There is no sign of a reversal in the CAPM and Fama and French alphas – they are lower than those from the Carhart model and not statistically significant. Finally, I looked at the long-term performance of the spread portfolio also from the perspective of characteristics-matched long-term buy and hold returns. Again, there is no indication of abnormal performance.

To complement the tests described above, I have reproduced Table XI using a different sorting variable: weight changes averaged over follower funds (funds with 4-factor alphas outside top 5%). None of the portfolios boasts abnormal returns. In all cases, alphas are insignificant. After controlling for the Fama-French and Carhart factors, the spread portfolio delivers only about 5 basis points per month, with the t-statistic of about 0.45. These results nicely correspond to evidence exhibited in Table III: follower weight changes do not help in predicting future portfolio decisions of other funds.

6 Conclusions

The present paper provides evidence of cross-autocorrelations in trades of mutual funds. I show that funds "follow the leaders:" trades of well performing funds are statistically and economically important determinants of subsequent portfolio decisions of the remaining managers. Controlling for other variables, for every dollar that leaders invest in the given stock, other funds additionally invest 15 to 30 cents in the subsequent quarter. I present evidence that poorly performing funds engage in mimicking more than funds with better performance.

Informational contents of leader trades influences the strength of mimicking. Trades of the leader funds that are more extreme elicit larger responses than more subdued trades. Also, trades in stocks that are less visible and for which informational asymmetries are likely to be large (small stocks, stocks followed by few analysts) lead to more mimicking. These results indicate that followers believe that leaders have superior information or better stock-picking ability. The edge of the best managers should be more apparent in trades in more opaque companies, and such trades lead to more mimicking. Interestingly, the effect is clearly visible in spite of the higher transaction costs associated with following leaders into small, poorly covered stocks.

The portfolio strategy that goes long in the stocks that leaders bought and short in those they sold delivers 3- and 4-factor alphas of the order of 35 basis points per month. When portfolio returns are characteristics-matched on past returns, size, and market-to-book, the spread portfolio still earns positive returns of the order of 0.16% per month, but these abnormal returns are not significant. Lack of significance does not mean that the mimicking strategy is unattractive. Some fund investors may care more about alphas than about characteristics-matched returns. Moreover, following the leaders could help funds reduce their research expenses. Lastly, there may be reputational benefits for funds with portfolios similar to those of the current leaders.

The results of this study could be interpreted within the following framework. My findings suggest that follower funds believe that leaders have better skill or information. Potentially, leaders are not able to fully impound their new information into stock prices: they may not be large enough, or decide against a large investment for reasons of diversification. Leaders' private information is revealed when they disclose their portfolio composition. At this stage, the information is available to all market participants. Followers then compete with (bid against) each other and jointly move prices to their fundamental levels. In result, stocks in leaders' portfolios appreciate. This may explain the short-term persistence of best fund performance, documented e.g. in Bollen and Busse (2005), Cohen, Coval, and Pastor (2005), or Spiegel, Mamaysky, and Zhang (2005).

Finally, my results suggest a possible link between follow the leader behavior and short-term momentum in stock returns. The mimicking mechanism I propose implies cross-autocorrelations in trades and I provide evidence that such correlations indeed exist in the data. To the extent that the correlated trades have price impact, they may drive momentum. Other evidence I present here points in that direction. The follow the leader the effect is stronger for small stocks and stocks with poor analyst coverage. Hong, Kubik, and Stein (2000) document that momentum is also stronger for such stocks. In the last part of my paper I show that the mimicking strategy delivers substantial alphas and that these alphas are partly related to momentum. The magnitude this abnormal performance is much smaller than that of momentum (e.g., Jegadeesh and Titman, 1993), which may suggest that mimicking is only one source of that phenomenon. Another explanation is that I do not capture the full scope of the follow the leader effect. The measure of leadership I use here is noisy and may not perfectly coincide with market participants' believes. Moreover, I focus only on one source of information about leaders' trades: portfolio reports. There are many other sources, for example the media or informal networks. They may lead to substantially more mimicking and cause mimicking at frequencies higher than quarterly.

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Figure 1. Long term performance of the spread portfolio. At the end of each quarter t stocks are sorted on portfolio weight changes of leader funds (funds with 4-factor alphas in the top 5%). After τ months, a portfolio long in stocks with the highest weight changes and short in stocks with the lowest weight changes is constructed (i.e., the inception time is $t + \tau$). The portfolio is then held for 3 months. The figure below exhibits monthly 4-factor alphas on that portfolio as a function of months skipped, τ. The dotted lines indicate 95% confidence interval for the alphas.

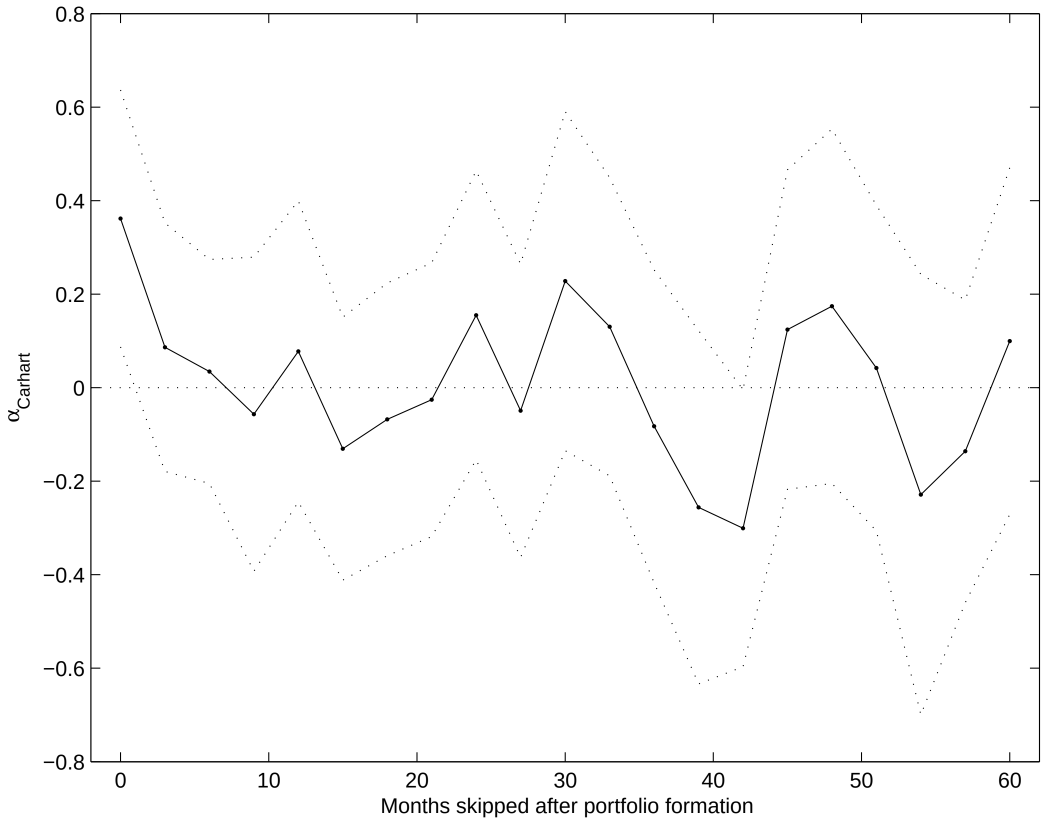

Table I. Summary statistics for different groups of funds. Each quarter, funds are ranked on their 4-factor alphas, estimated using 24 months of data. "Leaders" are funds with alphas in the top 5%; "remaining funds" are the compliment of the leader set. "Top 10" are 10 funds with the highest alphas. "Above median" are those whose alphas place them between the 50th and the 95th percentile of the performance distribution. The table summarizes the time-series averages of main attributes of the four fund groups. Assets are reported in millions of dollars, returns are in percentages. Returns are monthly averages computed over 1, 2, and 3 years.

	Leader funds (top 5%)	Remaining funds (not in top 5%)	Top 10 funds	Above median funds (50% to 95%)
Avg. assets	332.153	385.755	299.260	485.692
Median assets	143.234	99.225	170.532	143.384
# funds	35.5	1250.3	10.0	319.8
Avg rets (1 yr)	2.31	1.03	2.92	1.31
Avg rets (2 yrs)	2.38	1.05	2.99	1.37
Avg rets (3 yrs)	1.97	1.10	2.31	1.34
Avg. α_{3fct}	1.64	0.05	2.27	0.39
Avg. α_{4fct}	1.47	0.05	2.12	0.33

Table II. Funds follow industry leaders in their portfolio decisions. In all regressions, the dependent variable are portfolio weight changes, measured between the end of quarters $t-1$ and t and averaged over follower funds (funds with 4-factor alphas outside top 5%). The main explanatory variable are portfolio weight changes, measured between the end of quarters $t-2$ and $t-1$ and averaged over leader funds (funds with 4-factor alphas in top 5%). $w^{follower}$ are portfolio weights averaged over follower funds. Other explanatory variables include returns and turnover (ratio of stock volume over shares outstanding). Weight changes are in basis points, returns are in percentages. Each quarter, regressions are estimated on the cross section of stocks funds hold; the final coefficient estimates are from the Fama-MacBeth procedure. The number of stocks is the average over all cross sectional regressions. Newey-West corrected t-statistics are in parentheses.

Δw_{t-1}^{leader}	0.014	0.014	0.011	0.011	0.011	0.016	0.015	0.012	0.011	0.012
	(5.633)	(5.497)	(4.264)	(3.982)	(4.591)	(7.382)	(7.257)	(5.708)	(5.074)	(6.215)
$w_{t-1}^{follower}$						-0.099	-0.099	-0.102	-0.103	-0.103
						(-18.886)	(-19.106)	(-19.719)	(-19.625)	(-19.680)
$const$	0.821	-0.862	-1.816	-2.265	-1.744	5.903	5.570	5.361	4.826	5.368
	(3.802)	(-3.223)	(-4.890)	(-6.905)	(-4.891)	(13.880)	(14.889)	(12.055)	(12.180)	(11.014)
Ret_t		0.138	0.130	0.125	0.133		0.112	0.105	0.100	0.112
		(7.274)	(7.288)	(6.635)	(6.215)		(7.349)	(7.324)	(6.632)	(5.912)
Ret_{t-1}			0.093		0.094			0.119		0.121
			(5.574)		(5.467)			(6.978)		(6.299)
$Ret_{t-5\to t-1}$				0.028					0.046	
				(7.145)					(9.747)	
Trn_t					0.012					-0.075
					(0.060)					(-0.409)
Trn_{t-1}					-0.225					0.002
					(-1.384)					(0.018)
R^2	0.001	0.004	0.006	0.006	0.009	0.033	0.036	0.039	0.040	0.042
# stocks	4658.2	4587.9	4502.2	4227.5	4412.6	4339.6	4337.1	4268.5	4017.0	4188.9

Table III. Leader funds do not follow other funds. In all regressions, the dependent variable are portfolio weight changes, measured between the end of quarters $t-1$ and t and averaged over leader funds (funds with 4-factor alphas in top 5%). The main explanatory variable are portfolio weight changes, measured between the end of quarters $t-2$ and $t-1$ and averaged over funds with 4-factor alphas below top 5% (first 5 columns) and funds with alphas below the median (last 5 columns). w^{leader} are portfolio weights averaged over leader funds. Weight changes are in basis points, returns are in percentages. Each quarter, regressions are estimated on the cross section of stocks funds hold; the final coefficient estimates are from the Fama-MacBeth procedure. The number of stocks is the average over all cross sectional regressions. Newey-West corrected t-statistics are in parentheses.

	Non-leader funds (below top 5%)					Below median funds (below 50%)				
Δw_{t-1}^{other}	0.008	-0.003	0.001	-0.007	-0.012	-0.011	-0.017	-0.013	-0.018	-0.015
	(0.516)	(-0.216)	(0.095)	(-0.636)	(-0.878)	(-0.959)	(-1.612)	(-1.286)	(-1.651)	(-1.272)
w_{t-1}^{leader}			-0.153	-0.154	-0.153			-0.153	-0.154	-0.153
			(-18.220)	(-17.802)	(-17.387)			(-18.261)	(-17.885)	(-17.476)
$const$	1.142	-2.667	7.753	7.442	6.844	1.142	-2.752	7.758	7.415	6.812
	(4.749)	(-2.963)	(5.697)	(4.271)	(3.900)	(4.898)	(-2.983)	(5.779)	(4.258)	(3.879)
Ret_t		0.243		0.030	0.022		0.242		0.027	0.021
		(3.337)		(0.468)	(0.337)		(3.367)		(0.430)	(0.318)
Ret_{t-1}		0.053		0.126			0.058		0.130	
		(1.228)		(2.857)			(1.307)		(2.873)	
$Ret_{t-5\rightarrow t-1}$					0.067					0.068
					(3.155)					(3.198)
R^2	0.003	0.014	0.056	0.063	0.064	0.003	0.014	0.056	0.063	0.064
# stocks	1074.2	1020.2	949.4	923.9	852.8	1074.2	1020.1	949.3	923.9	852.9

Table IV. Following the leader: other variables. Regressions from Table II are reproduced for different proxies for fund actions, X. In all cases, variable X is measured across leaders (followers), that is, funds with 4-factor alphas in top 5% (outside top 5%). In the first two columns, X is the weight change for the aggregate portfolio of funds in the given subset. In the next three columns, X is dollar volume (in thousands), and the log of that quantity. In the last three columns, X is share volume (in thousands) and log of share volume. Weight changes are in basis points, returns are in percentages. Each quarter, regressions are estimated on the cross section of stocks funds hold; the final coefficient estimates are from the Fama-MacBeth procedure. The number of stocks is the average over all cross sectional regressions. Newey-West corrected t-statistics are in parentheses.

	$X = \Delta w^{aggregate}$		X =dollar volume		$X = \log(\$ \text{ vol})$	X =share volume		$X = \log(\text{shr.vol.})$
X_{t-1}^{leader}	0.010	0.009	0.283	0.204	0.068	0.264	0.162	0.073
	(3.651)	(3.239)	(4.938)	(3.721)	(7.388)	(3.559)	(2.983)	(7.395)
$X_{t-1}^{follower}$		-0.008		0.089	0.085		0.091	0.087
		(-13.102)		(6.693)	(12.813)		(3.854)	(12.737)
$const$	0.005	0.451	757.492	356.252	0.976	2.595	15.098	0.737
	(0.217)	(8.311)	(6.561)	(4.097)	(5.592)	(0.302)	(2.543)	(5.217)
Ret_t		0.015		13535.388	0.040		1077.244	0.034
		(3.750)		(6.934)	(11.814)		(7.167)	(12.247)
Ret_{t-1}		0.016		12526.733	0.034		1183.373	0.029
		(4.800)		(6.052)	(10.544)		(3.751)	(10.568)
R^2	0.007	0.017	0.006	0.032	0.029	0.014	0.067	0.031
# stocks	3638.3	3318.2	3306.2	2357.8	2357.8	3537.8	2377.1	2377.1

Table V. Non-linearities in fund reaction to stock returns. The dependent variable are portfolio weight changes between quarters $t-1$ and t, averaged over follower funds (funds with 4-factor alphas outside top 5%). The main explanatory variable are portfolio weight changes between quarters $t-2$ and $t-1$, averaged over leader funds (funds with 4-factor alphas in top 5%). $w^{follower}$ are portfolio weights averaged over follower funds. The "top 5% dummy" takes the value of 1 for stocks with past returns, measured over quarter t (first 3 columns) or between quarters $t-5$ and $t-1$ (last 3 columns), in the top 5% of the cross-sectional return distribution. Weight changes are in basis points, returns (but not higher order terms of returns) are in percentages. Each quarter, regressions are estimated on the cross section of stocks funds hold; the final coefficient estimates are from the Fama-MacBeth procedure. The number of stocks is the average over all cross sectional regressions. Newey-West corrected t-statistics are in parentheses.

Δw_{t-1}^{leader}	0.012	0.012	0.012	0.011	0.011	0.012
	(5.699)	(5.660)	(5.705)	(5.041)	(5.028)	(5.083)
$w_{t-1}^{follower}$	-0.103	-0.103	-0.103	-0.105	-0.104	-0.104
	(-19.714)	(-19.748)	(-19.717)	(-19.596)	(-19.594)	(-19.660)
$const$	5.450	5.327	5.401	4.943	4.812	4.933
	(11.856)	(11.548)	(11.652)	(11.194)	(11.595)	(11.841)
Ret_t	0.104	0.105	0.104	0.097	0.098	0.100
	(7.228)	(7.190)	(7.265)	(6.678)	(6.678)	(6.618)
Ret_{t-1}	0.141	0.142	0.135			
	(7.352)	(6.984)	(8.026)			
Ret_{t-1}^2	-6.335					
	(-4.168)					
Ret_{t-1}^3		-6.230				
		(-2.470)				
top 5% dummy			-3.016			
			(-3.412)			
$Ret_{t-5\to t-1}$				0.060	0.055	0.051
				(9.921)	(9.051)	(9.802)
$Ret_{t-5\to t-1}^2$				-1.247		
				(-2.627)		
$Ret_{t-5\to t-1}^3$					-0.305	
					(-1.392)	
top 5% dummy						-1.492
						(-1.764)
R^2	0.040	0.039	0.039	0.041	0.040	0.040
# stocks	4268.5	4268.5	4268.5	4017.0	4017.0	4017.0

Table VI. Funds follow Honor Roll leaders in their portfolio decisions. Funds are divided into two groups: leaders (funds on the Forbes Honor Roll for the given year) and followers (the remaining funds). In all regressions, the dependent variable are portfolio weight changes, measured between the end of quarters $t-1$ and t and averaged over the follower funds. The main explanatory variable are portfolio weight changes, measured between the end of quarters $t-2$ and $t-1$ and averaged over leader funds. $w^{follower}$ are portfolio weights averaged over follower funds. Other explanatory variables include returns and turnover. Weight changes are in basis points, returns are in percentages. Each quarter, regressions are estimated on the cross section of stocks funds hold; the final coefficient estimates are from the Fama-MacBeth procedure. The number of stocks is the average over all cross sectional regressions. Newey-West corrected t-statistics are in parentheses.

Δw^{leader}_{t-1}	0.021	0.018	0.017	0.025	0.020	0.020
	(3.754)	(3.031)	(3.016)	(4.499)	(3.599)	(3.643)
$w^{follower}_{t-1}$				-0.093	-0.098	-0.098
				(-15.367)	(-16.110)	(-16.210)
const	1.258	-1.247	-1.136	6.003	5.699	5.639
	(6.011)	(-4.148)	(-3.773)	(10.012)	(9.723)	(8.344)
Ret_t		0.105	0.109		0.081	0.090
		(7.077)	(5.608)		(7.394)	(5.287)
Ret_{t-1}		0.060	0.062		0.087	0.087
		(4.762)	(4.550)		(6.486)	(5.734)
Trn_t			0.048			0.021
			(0.231)			(0.112)
Trn_{t-1}			-0.306			-0.051
			(-1.737)			(-0.352)
R^2	0.000	0.004	0.008	0.034	0.039	0.044
nr stocks	4721.8	4555.6	4465.0	4409.4	4330.1	4250.5

Table VII. Following in stocks with many and few news events. Stocks are divided into two groups: "news stocks" (stocks with the absolute value of the EPS forecast change equal to or above the median) and "no news" stocks (stocks with absolute value of the change below the median). The top panel presents regressions run on news stocks only (first 3 columns) or no-news stocks only (last 3 columns). The dependent variable are portfolio weight changes, measured between the end of quarters $t-1$ and t and averaged over follower funds (funds with 4-factor alphas below top 5%). The main explanatory variable are portfolio weight changes, measured between the end of quarters $t-2$ and $t-1$ and averaged over leader funds (funds with 4-factor alphas in top 5%). $w_{t-1}^{follower}$ are lagged portfolio weights, averaged over follower funds. Other explanatory variables include returns and turnover. Each quarter, regressions are estimated on the cross section of stocks funds hold; the final coefficient estimates are from the Fama-MacBeth procedure. The number of stocks is the average over all cross sectional regressions. The bottom panel reports Fama-MacBeth estimates of the differences in the leader coefficients for news and no news stocks. Weight changes are in basis points, returns are in percentages. Newey-West corrected t-statistics are in parentheses.

	News stocks:			No news stocks:		
Δw_{t-1}^{leader}	0.011	0.011	0.011	0.009	0.009	0.010
	(4.383)	(5.405)	(5.312)	(2.649)	(2.958)	(3.069)
$w_{t-1}^{follower}$		-0.103	-0.104		-0.084	-0.085
		(-10.869)	(-10.944)		(-9.007)	(-8.922)
const	-1.702	5.522	6.416	-0.651	5.122	5.305
	(-6.299)	(8.085)	(8.243)	(-2.916)	(5.936)	(5.641)
Ret_t		0.117	0.121		0.175	0.171
		(7.382)	(7.258)		(6.942)	(6.831)
Ret_{t-1}		0.142	0.143		0.160	0.168
		(10.194)	(9.725)		(5.907)	(5.243)
Trn_t			-0.371			0.274
			(-1.218)			(1.274)
Trn_{t-1}			-0.208			-0.286
			(-1.180)			(-1.524)
R^2	0.002	0.043	0.049	0.002	0.042	0.049
# stocks	1610.4	1571.9	1558.5	1569.8	1530.1	1508.1
Differences between Δw_{t-1}^{leader} coefficients:						
	0.002	0.002	0.001			
	(0.532)	(0.491)	(0.331)			

Table VIII. Follower characteristics. In all regressions in the top panel, the dependent variable are portfolio weight changes, measured between the end of quarters $t-1$ and t. In the first two columns, the changes are averaged over below and above median funds (funds with 4-factor alphas below/ above the cross-sectional median). In the next two columns, the averages are over small (bottom 20%) and large (top 20%) funds. In the last two columns, the averages are taken over young (at most 3 years old) and old (at least 10 years old) funds. w^{other} are portfolio weights averaged over the set of funds indicated in the column. The main explanatory variable are portfolio weight changes, measured between the end of quarters $t-2$ and $t-1$ and averaged over leader funds (funds with 4-factor alphas in top 5%). Other explanatory variables include returns and turnover. Each quarter, regressions are estimated on the cross section of stocks funds hold; the final coefficient estimates are from the Fama-MacBeth procedure. The number of stocks is the average over all cross sectional regressions. The bottom panel reports Fama-MacBeth estimates of the differences in the leader coefficients. Weight changes are in basis points, returns are in percentages. Newey-West corrected t-statistics are in parentheses.

	α <median	α >median	Small	Large	Young	Old
Δw^{leader}_{t-1}	0.012	0.008	0.014	0.007	0.015	0.010
	(6.215)	(3.152)	(2.197)	(4.548)	(3.524)	(6.045)
w^{other}_{t-1}	-0.103	-0.135	-0.172	-0.067	-0.159	-0.098
	(-19.680)	(-15.467)	(-15.325)	(-9.623)	(-12.885)	(-15.112)
$const$	5.368	8.464	24.586	1.688	10.937	4.747
	(11.014)	(10.010)	(9.649)	(3.475)	(6.867)	(8.987)
Ret_t	0.112	0.108	0.122	0.046	0.094	0.093
	(5.912)	(4.275)	(3.010)	(3.582)	(5.633)	(4.196)
Ret_{t-1}	0.121	0.114	0.193	0.055	0.124	0.119
	(6.299)	(5.465)	(7.318)	(4.365)	(7.892)	(5.377)
Trn_t	-0.075	-0.490	-1.602	-0.479	-0.446	-0.314
	(-0.409)	(-1.699)	(-1.890)	(-1.776)	(-1.223)	(-1.437)
Trn_{t-1}	0.002	0.393	0.703	0.413	0.014	0.260
	(0.018)	(1.395)	(1.095)	(1.752)	(0.070)	(1.399)
R^2	0.042	0.058	0.058	0.037	0.064	0.045
# stocks	4188.9	3149.6	1919.5	3284.4	2694.4	3324.6
Differences in Δw^{leader}_{t-1} coefficients:						
	0.004		0.007		0.004	
	(2.081)		(1.080)		(1.145)	

Table IX. Mimicking portfolio initiations and deletions. In all regressions, the dependent variable are portfolio weight changes, measured between the end of quarters $t-1$ and t and averaged over follower funds (funds with 4-factor alphas outside top 5%). The main explanatory variable are portfolio weight changes, measured between the end of quarters $t-2$ and $t-1$ and averaged over leader funds (funds with 4-factor alphas in top 5%). In the first 3 columns, only leader trades that are initiations or deletions are considered. In the last 3 columns, only leader trades that are not initiations or deletions are considered. $w^{follower}$ are portfolio weights averaged over follower funds. Other explanatory variables include returns and turnover. Each quarter, regressions are estimated on the cross section of stocks funds hold; the final coefficient estimates are from the Fama-MacBeth procedure. The number of stocks is the average over all cross sectional regressions. The bottom panel reports Fama-MacBeth estimates of the differences in the leader fund coefficients. Weight changes are in basis points, returns are in percentages. Newey-West corrected t-statistics are in parentheses.

	Initiations and deletions:			Other trades:		
Δw^{leader}_{t-1}	0.012	0.012	0.012	0.007	-0.001	-0.001
	(6.092)	(7.819)	(7.483)	(1.626)	(-0.125)	(-0.148)
$w^{follower}_{t-1}$		-0.103	-0.103		-0.102	-0.103
		(-19.732)	(-19.685)		(-19.714)	(-19.680)
$const$	0.804	5.354	5.366	0.841	5.354	5.360
	(3.730)	(12.034)	(10.991)	(3.877)	(12.084)	(11.029)
Ret_t		0.105	0.112		0.105	0.112
		(7.344)	(5.925)		(7.342)	(5.929)
Ret_{t-1}		0.119	0.120		0.120	0.122
		(7.006)	(6.332)		(7.106)	(6.390)
Trn_t			-0.076			-0.077
			(-0.414)			(-0.422)
Trn_{t-1}			0.002			0.001
			(0.012)			(0.011)
R^2	0.001	0.039	0.042	0.000	0.039	0.042
# stocks	4658.2	4268.5	4188.9	4658.3	4268.6	4189.0
Differences in Δw^{leader}_{t-1} coefficients:						
	0.005	0.012	0.013			
	(1.061)	(2.943)	(2.753)			

Table X. Mimicking depends on stock size, number of analysts, and idiosyncratic volatility. The dependent variable are portfolio weight changes between quarters $t-1$ and t, averaged over follower funds (funds with 4-factor alphas below top 5%). The main explanatory variable are portfolio weight changes between quarters $t-2$ and $t-1$, averaged over leader funds (funds with 4-factor alphas in top 5%) and interacted with log of company market capitalization in thousands of dollars (first 3 columns), log of the number of analysts following the given stock (middle 3 columns), and idiosyncratic volatility from the Fama-French model (last 3 columns). $w^{follower}$ are portfolio weights averaged over follower funds. Other variables include returns and turnover. Weight changes are in basis points, returns are in percentages. Each quarter, regressions are estimated on the cross section of stocks funds hold; the final coefficient estimates are from the Fama-MacBeth procedure. The number of stocks is the average over all cross sectional regressions.

	V is log($MktCap$):			V is log($1+\#analysts$)			V is σ_{3fct}		
Δw^{leader}_{t-1}	0.038	0.047	0.050	0.029	0.026	0.025	-0.004	-0.006	-0.006
	(2.483)	(3.405)	(3.478)	(3.415)	(3.565)	(3.541)	(-0.882)	(-1.374)	(-1.343)
$\Delta w^{leader} \times V$	-0.002	-0.003	-0.003	-0.008	-0.007	-0.006	0.163	0.180	0.183
	(-1.606)	(-2.661)	(-2.750)	(-2.549)	(-2.726)	(-2.572)	(2.951)	(3.913)	(3.751)
$w^{follower}_{t-1}$		-0.085	-0.086		-0.086	-0.086		-0.085	-0.086
		(-12.242)	(-12.545)		(-12.288)	(-12.571)		(-12.221)	(-12.404)
$const$	0.822	3.790	3.956	0.819	3.817	3.955	-1.043	3.527	3.825
	(3.736)	(6.771)	(6.871)	(3.789)	(6.783)	(6.878)	(-5.439)	(6.263)	(6.754)
Ret_t		0.100	0.107		0.100	0.107		0.099	0.105
		(7.797)	(6.320)		(7.757)	(6.306)		(6.968)	(5.822)
Ret_{t-1}		0.113	0.114		0.113	0.114		0.109	0.109
		(6.738)	(6.239)		(6.767)	(6.249)		(6.084)	(5.860)
Trn_t			-0.074			-0.075			-0.131
			(-0.412)			(-0.415)			(-0.773)
Trn_{t-1}			-0.025			-0.025			-0.029
			(-0.182)			(-0.189)			(-0.235)
R^2	0.001	0.037	0.041	0.001	0.038	0.042	0.001	0.040	0.044
# stocks	4652.1	4213.9	4140.3	4658.2	4218.4	4140.3	3921.0	3695.7	3631.4

Table XI. Performance of portfolios based on leader trades. At the end of each quarter, stocks are ranked on their leader weight changes, where leaders are funds with 4-factor alphas in the top 5%. Ranked stocks are split into 5 value-weighted portfolios. The first panel presents the average weight changes in the ranking period. The second panel summarizes the performance of the portfolios and reports monthly average returns and alphas. The third panel reports the differences between monthly returns on the 5 portfolios and control portfolios of stocks matched on different subsets of three characteristics: size (Mcap), market-to-book (M/B), and momentum (MOM, measured as past year's return). To create the control portfolios, each stock is matched with equal-weight portfolio of stocks in the same decile of the characteristics of interest.

Leader weight changes per portfolio

	1	2	3	4	5
Avg. Δw^{leader}	-1.336	-0.257	-0.028	0.229	1.420
Std. Δw^{leader}	0.357	0.092	0.037	0.100	0.360

Monthly performance of leader-fund based portfolios

	1	2	3	4	5	5-1
Average	1.055	1.194	1.232	0.977	1.405	0.351
Std	5.089	5.144	5.205	5.300	5.060	2.298
α_{CAPM}	-0.106	0.037	0.069	-0.197	0.264	0.371
	(-0.984)	(0.333)	(0.603)	(-1.482)	(2.328)	(2.777)
$\alpha_{FamaFrench}$	-0.084	0.098	0.091	-0.212	0.350	0.434
	(-0.814)	(0.894)	(0.762)	(-1.525)	(2.773)	(3.136)
$\alpha_{Carhart}$	-0.141	0.091	0.197	-0.226	0.221	0.362
	(-1.311)	(0.845)	(1.616)	(-1.670)	(1.856)	(2.582)

Abnormal characteristics-matched monthly returns

	1	2	3	4	5	5-1
MCap+M/B	-0.101	0.128	0.002	-0.225	0.208	0.267
	(-0.815)	(1.277)	(0.018)	(-1.202)	(2.457)	(2.248)
MCap+MOM	-0.050	0.074	-0.044	-0.235	0.202	0.234
	(-0.426)	(0.806)	(-0.411)	(-1.404)	(2.418)	(2.224)
MCap+M/B+MOM	0.034	0.175	0.003	-0.200	0.186	0.160
	(0.291)	(1.329)	(0.024)	(-0.875)	(1.517)	(1.119)