Essays on Mutual Funds and Stock Returns

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Abstract

This dissertation includes three essays on mutual funds and stock returns, specifically on active mutual funds' style change and skill, on passive or index funds' fees and investors' sensitivity, and on stock market exits and return anomaly, using econometric methods and large mutual fund and individual stock datasets.

The first chapter shows that active equity funds deliberately alter their factor loadings rather than maintaining a constant style. Changes are larger following quarters in which funds either under- or out-perform other funds based on returns or fund flows. Motivated by this observation, we identify a new measure of manager skill, which we call "tactical investment skill." It captures a manager's ex-ante observable ability to increase future returns through loadings changes. We show that high-skill managers outperform their low-skill peers in the following month in terms of raw returns and alphas. This outperformance is more pronounced following quarters with large loadings changes.

The second chapter identifies index funds as a special setting to estimate investors' fee sensitivity. Before-fee returns of different funds that track the same index should all equal to the index return and thus fees become a major consideration. There is a more steady and larger decline in asset-weighted average expense ratio, compared with the simple average. Investors concentrate more on low-fee funds. The further examination shows that one basis point difference in monthly fund fees is negatively related with a monthly flow difference of 0.12% for S&P 500 index funds.

The third chapter[1] predicts the two most common stock market exits – mergers and drops – using logit models based on firm-level variables and analyzes the returns of stocks that have high exit probabilities. Such analysis is important for investors given that frequent exits are partly responsible for the large U.S. listing gap (Doidge, Karolyi, and Stulz (2017)). High merger probability stocks have positive three-factor alphas and lower-than-average volatility. Firms with high drop probabilities have anomalously negative three-, four-, and five-factor alphas between -1.8% and -4% per month. Results are robust to controlling for the effects of skewness, volatility, and turnover on returns.

[1]For the third chapter, due to copyright restrictions, please see "Two different exits: Prediction and performance of stocks that are about to stop trading", Ting Bai, Jens Hilscher, and Yitian Xiao, Quarterly Journal of Finance, Vol. 13, No. 1 (2023), Copyright @ 2023 and World Scientific Publishing Company and Midwest Finance Association.

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Contents

Chapter 1

Unencumbered by style: Why do funds change factor loadings and does it help?[1]

[1]Coauthored with Jens Hilscher, UC Davis, and Anna Scherbina, Brandeis University.

1.1 Introduction

Style is perhaps the most salient attribute of a mutual fund. Morningstar's ubiquitous style box is a prominent reflection of potential investors' attention to style. However, as we show in this paper, managers do not always adhere to a constant style but alter the fund's style tilt at different times. While some managers may change styles for agency or behavioral reasons, a subset of high-skill managers may flexibly choose to alter the style in order to increase future returns.

The purported ability to anticipate future developments is a selling point used by actively managed funds to distinguish themselves from passive index funds. For example, a March 8, 2023 Morgan Stanley Insights article states that "active management is forward-looking" and, in comparison, passively managed funds fail to make "tactical adjustments based on market conditions." It also claims: "we are, in fact, trying to forecast the future."[2] These statements echo a long-standing sentiment of active fund managers that passive investment management is "mediocre" and active management has the capacity to do better. For example, the tagline of the December 8, 2013 *New York Times* interview, fund manager Robert Olstein said: "If you rely on index funds, you're celebrating mediocrity."[3] Obviously omitted in the marketing materials is a discussion of incentive problems associated with active management.

Fund returns and fund flows are two of the most prominent and easily observable metrics of performance of an actively managed fund. Fund managers wish to maximize fund flows and returns and, consequently, the fund's total net assets, on which fund fees are charged. Fund managers care about return not only because return helps grow assets under management, but also because return matters for their reputation and career development (Chevalier, Judith, and Glenn Ellison (1999)). As is well-documented, fund flows respond to returns since fund investors view prior returns as a proxy of fund managers' skill and a predictor

[2] `https://www.morganstanley.com/im/en-pt/institutional-investor/insights/articles/case-for-stable-risk-adjusted-returns-why-now.html`.

[3] In the interview, Robert Olstein also said of index investing: "The professors don't advise their students to settle for mediocrity at school ... why do it in investing?"

of future returns (see, e.g., Ippolito (1992), Chevalier and Ellison (1997), Sirri and Tufano (1998), Lynch and Musto (2003)).

One way to improve returns and fund flows is by flexibly making stock selections, in particular without a constraint to keep the style constant. Strategically altering weights in certain stocks may increase exposure to style areas where the fund manager sees good prospects. In addition to selecting stocks that may cross style categories, managers may also be engaging in factor timing (see, e.g. Daniel, Grinblatt, Titman, and Wermers (1997)).[4] More starkly, style changes may affect flows directly because investors may develop preferences for specific styles (Cooper, Gulen, and Rau (2005)) or because investors may be watching closely whether or not managers make active changes to the investment strategy in order to optimize the style of the fund and increase future returns (Lynch and Musto (2003)). Managers may also increase and decrease portfolio allocations to specific styles for behavioral reasons, such as feedback trading (e.g., Frijns, Gilbert, and Zwinkels (2016) and Busse, Ding, Jiang, and Tang (2022)). Finally, underperforming managers may shift portfolios to riskier stocks later in the year for incentive reasons due to the convex flow-return relation (e.g., Chevalier and Ellison (1997)). To sum up, managers may alter fund styles as an outcome of an unconstrained bottom-up stock selection process, because they engage in factor timing, because they cater to investor style preferences, as a result of factor feedback trading, or for incentive reasons.

Two questions naturally arise: First, do fund managers react to prior fund flows and returns by changing styles? Second, do such style changes have an effect on fund returns? Specifically, can we identify which funds have the skill to deliver future outperformance through style changes and which other funds' style changes may result in lower returns?

We begin by exploring if managers react to returns and flows by changing investment styles, which we measure by the fund's factor loadings on market, size, value and momentum

[4]Changing factor exposures can also affect Jensen's alpha, which is the performance measure used most by mutual fund investors (e.g., Berk, Jonathan B., and Jules H. Van Binsbergen (2016) and Barber, Huang, and Odean (2016)), which would, in turn, affect flows.

factors of Fama and French (1993) and Carhart (1997).[5] For all active domestic diversified equity funds, we estimate quarterly loadings on the four factors using daily data of fund returns and adjust these loadings for the loadings of the factor-neutral portfolios (Lettau, Ludvigson, and Manoel (2018)). If fund managers react to past returns and flows by unconstrained stock selection that results in changing styles, there should be evidence that factor loadings change in response to flows and returns. Since the direction of loadings changes varies with market conditions, we focus on the magnitude of the absolute value of the loadings changes.

We identify a U-shaped relationship between both flows and returns (alphas) and next period style changes. The pattern suggests a highly non-linear response to flows and returns. Returns and flows that are large in terms of magnitude result in style changes, and more extreme flows or returns result in larger style changes, controlling for the loadings levels, volatility, fund fixed effects, and time effects. Funds may react to prior outflows and poor returns by changing the investment strategy, hoping to increase returns and reduce outflows. Funds with high returns may be rebalancing their portfolios if the previously underpriced stocks have moved to more reasonable valuations, and funds with large inflows may be distributing these inflows unevenly across style areas. We also find that the reaction of fund managers to extreme past returns is stronger than the reaction to extreme past fund flows. A same-size rank shift in return as in fund flow results in a four to five times larger style shift.

We check that large loadings changes are the result of deliberate trading decisions rather than individual stock holdings mechanically shifting their factor loadings. Specifically, we show that funds with larger loadings changes have a significantly higher portfolio turnover than funds with lower changes in factor loadings.

Having documented that funds deliberately change their styles, we next ask if such style changes can be beneficial. As discussed above, if style changes are implemented in response

[5]Throughout the paper, we use the terms "style" and "factor loadings" interchangeably.

to incentives, investor preferences or behavioral reasons, they are unlikely to improve future returns. But if skilled managers engage in the bottom-up stock selection unconstrained by style or even in deliberate factor timing, they may be able to increase future returns with the help of style shifts.

We want to capture the variation in the ability of active fund managers to adjust their factor exposures in anticipation of future factor movements. To this end, we propose a new measure of manager skill based on a manager's demonstrated track record of achieving higher future returns by changing factor loadings. We use rolling five-year windows of quarterly data and regress the fund's excess return on the last quarter's style change. The regression coefficient from these regressions captures a manager's ability to benefit from the changing market conditions, and we call it a "tactical investment skill." A manager who was able to increase future returns by changing the fund style will have a positive skill measure, and a manager who has in the past destroyed investor value by changing the fund style would have a negative skill measure.

We find that managers who have a track record of successfully using style changes to increase future returns, i.e. managers with high "tactical investment skill," outperform their peers. The portfolio containing funds in the top quintile of this skill measure outperforms the lowest skill quintile portfolio by 1.58% per year; the t-statistic is 2.75. The corresponding four-factor alpha is also quite high, 1.09%, and statistically significant, and these magnitudes exceed a typical fee charged by actively managed funds. We furthermore show that the outperformance of high-skill managers as compared to their low-skill colleagues is most pronounced following quarters in which both groups have large loadings changes. Among the funds in the top quintile of loadings changes, managers in the top quintile of tactical skill outperform managers in the bottom quintile of skill by a statistically significant 1.90% per year (four-factor alpha of 1.31%).

To summarize, our results indicate that managers react to extreme flows and returns by changing factor loadings. For a subset of managers this flexibility to change styles is beneficial, while it is less helpful for others. Managers who are skilled to take advantage of the style flexibility earn higher future returns than their low-skill counterparts, in particular following large changes in fund's factor loadings. Being unencumbered when it comes to style can thus be useful.

1.1.1 Related literature

This paper adds to the literature that explores mutual funds' time-varying styles. As mentioned above, funds may change their styles for several reasons, such as catering to investor preferences, incentive reasons, behavioral biases, factor timing, or unconstrained stock selection that spans style categories. While the first three reasons are not expected to increase returns, the latter two may result in higher future performance for skilled managers.

While the literature on mutual funds' catering to investor style preferences is relatively recent, Cooper, Gulen, and Rau (2005) make a notable contribution. This paper shows that a lower mean fund flow in the past six months is associated with a higher probability of the fund changing its name, for example to reflect current hot styles that have earned high recent returns. However, some funds' actual styles could be different from what the new name indicates as funds have not actually changed the style to be consistent with the new names. Our paper instead focuses on actual style changes, as measured by changes in factor loadings.

The literature on managers changing the riskiness of a fund's portfolio in response to incentives is more established. Due to a convex flow-performance relation, the literature has shown that funds that underperform their peers increase the riskiness of their portfolios later in the year (e.g., Brown, Harlow, and Starks (1996) and Chevalier and Ellison (1997)).[6] Han, Roussanov, and Ruan (2022) further show that risk-shifting funds that increase portfolio risk later in the year do so by allocating higher portfolio weights to stocks with the largest co-

[6] Huang, Sialm, and Zhang (2011) use a holdings-based measure of risk-shifting and show that funds with fluctuating portfolio risk subsequently underperform funds with stable risk levels. Brown, Harlow, and Zhang (2009) show that the most style-consistent funds outperform less consistent funds.

movement (betas) with the funds' respective benchmarks, while also reducing the exposure to the low-beta stocks. Therefore, such behavior would result in fluctuating fund betas. We check that our results are not driven by the later quarters.

Another incentive-based explanation for changes in fund styles is that mutual funds change styles after experiencing poor performance to signal a change in investment strategy. Chan, Chen, and Lakonishok (2002) show that funds in the bottom quintile of compounded returns over the past two years have a larger change in HML and SMB loadings in the next year than other funds. Lynch and Musto (2003) find that funds with returns in the bottom quartile change factor loadings more or are more likely to change managers than funds in other quartiles. Funds use loadings changes or new managers to signal a new investment strategy to stop investors from leaving after poor returns. Moreover, Vidal-García and Vidal (2022) show that, when experiencing relatively low returns within its category (based on self-declared investment policy), a fund is more likely to change its category.

In contrast to these papers, we examine factor loadings changes motivated by *both* prior flows and returns. We find that both independently cause loadings changes. Fund managers appear to change styles both because they are trying to increase flows, as the above papers suggest, but also in order to increase future returns. As such, our results are not simply a manifestation of the well-known flow-return relationship. Second, extending from the method of mean comparison used in Chan, Chen, and Lakonishok (2002) and Lynch and Musto (2003), we treat return as a continuous variable by using percentile rank or including return in the model directly. This is in contrast to using return to define a categorical variable. Using our approach we find important non-linear effects by identifying marginal effects for different groups of both flow and return. Adding to previous findings, we observe that large positive returns are also associated with future loadings changes.

There are also behavioral explanations for shifting styles, for example style feedback trading as modeled by Barberis and Shleifer (2003). Consistent with the model's predictions, Frijns, Gilbert, and Zwinkels (2016) find evidence of both positive and negative style feedback trading for 77% of U.S. domestic equity funds. Similarly, Busse, Ding, Jiang, and Tang (2022) show that mutual funds engage in feedback trading with respect to past aggregate market returns, reducing portfolios' market beta following poor market returns and increasing it following high market returns. However, there is little evidence that such trading results in elevated returns.

Fund styles may also change as a result of factor timing. The literature has investigated fund managers' ability to time the market as well as other priced factors. While some papers do not find that fund managers are able to time the market (e.g., Henriksson and Merton (1981), Daniel, Grinblatt, Titman, and Wermers (1997), Chang and Lewellen (1984), Henriksson (1984), Chan, Chen, and Lakonishok (2002), Elton, Edwin J, Martin J Gruber, and Christopher R Blake (2012)) others, using different samples and specifications, do find evidence in favor of the market-timing ability. Examples include Bollen and Busse (2001), when they use daily but not monthly data, Busse, Ding, Jiang, and Wu (2023), who use daily return data to estimate daily-frequency betas with a dynamic conditional correlation approach, Mamaysky, Spiegel, and Zhang (2008), who use Kalman filter on monthly betas, and Kacperczyk, Nieuwerburgh, and Veldkamp (2014), who document the market timing ability for a subset of skilled managers, and Jiang, Yao, and Yu (2007), who estimate the timing ability from the holdings data. Moreover, Swinkels and Tjong-A-Tjoe (2007) show some evidence of funds' ability to time other priced factors.

Furthermore, managers may change factor loadings by not constraining themselves to a particular category when selecting stocks. If a manager identifies investment opportunities that are disproportionately in a different category than the existing portfolio holdings, the fund's factor loadings will change. Wermers (2012) identifies style drift from portfolio holdings rather than from the regression of returns on factors and finds that managers who have a good stock-picking track record have higher style drifts than other managers. After decomposing style drift into active (deliberate) and passive style drift, he finds that managers with greater active style drift, on average, outperform other managers. This result is in contrast to Brown, Harlow, and Zhang (2009), who use both portfolio holdings and return regressions to estimate style consistency, and find that more style-consistent funds tend to outperform the less style-consistent funds. Our evidence supports both sets of results. We are able to identify funds that consistently improve future performance through style changes, perhaps due to their factor timing abilities as well as unconstrained stock picking, but we also identify managers whose style changes lead them to consistently underperform, possibly due to low skill or incentive problems.

Finally, styles may also drift naturally if a manager does not rebalance the portfolio to maintain a constant style (what Wermers (2012) refers to as passive style drift). However, Wermers (2012) finds that active managers exhibit larger style changes and that the active style drift represents a substantial contribution to the total style drift. We show that the changes in factor betas are accompanied by high portfolio turnover, indicating that it is largely deliberate trading decisions that result in fund style changes.

By showing frequent and widespread changes in funds' factor loadings, this paper also adds to the literature on non-constant fund betas that advocates estimating funds' factor loadings using daily returns over shorter estimation windows rather than monthly returns. Annaert and Van Campenhout (2007) use daily returns for European equity funds distributed in Belgium and show that the returns exhibit frequent structural breaks in their style exposures. Other papers point out that assessing managers' market timing ability from monthly returns may be problematic. Goetzmann, Ingersoll, and Ivković (2000) and Bollen and Busse (2001) point out the pitfalls of using monthly returns to measure managers' market timing ability, which may be occurring at a higher frequency. Busse, Ding, Jiang, and Tang (2022) furthermore show that monthly-frequency regressions may give a researcher the wrong impression that fund managers are skilled at market timing, while they may be instead engaged in higher-frequency feedback trading in response to recent market returns.

In documenting that some managers exhibit skill in achieving future outperformance through style shifts, we contribute to the literature on managerial skill. Generally, this literature shows a positive relation between the level of activity of a mutual fund manager and subsequent returns. For example, Cremers and Petajisto (2009) define active share as the share of holdings deviating from benchmarks and find that funds with high active share outperform benchmarks. Amihud and Goyenko (2013) identify a manager's activeness from the return history rather than holdings. They regress past returns on benchmark factors and show that the more active funds, those with the lowest regression R^2's, outperform the relatively passive funds with high R^2's. Pastor, Lubos, Robert F Stambaugh, and Lucian A Taylor (2017) document a positive relation between fund portfolio turnover and subsequent benchmark-adjusted return. Wermers (2012) finds that funds with large active style drift exhibit positive four-factor alphas. Busse, Ding, Jiang, and Wu (2023) show that managers who have demonstrated a high ability to time the market in a given month continue to outperform the low-ability managers in the future. Kacperczyk, Sialm, and Zheng (2005) show that funds whose portfolios are concentrated in a few industries, in which managers are likely to have informational advantage, exhibit better future performance. Our paper introduces a new measure, "tactical investment skill," based on the demonstrated ability to increase future returns through style changes and shows that this measure is related to performance.

The rest of the paper is organized as follows. Section 1.2 describes data construction and summary statistics. Section 1.3 discusses U-shaped patterns between past flow or return and style changes and our main results using a piecewise linear regression model to capture the nonlinear relationship between flow, return and style changes. Section 1.4 evaluates the impact of fund loadings changes, introduces our new measure of skill and shows that high-skill managers deliver higher returns. Section 1.5 concludes.

1.2 Data description

1.2.1 Data and variable construction

We use data from the Center for Research in Security Prices (CRSP) Survivor-Bias-Free US Mutual Fund Database. We use the mutual fund link variable from the MFLINKS database, and data on factor portfolio returns and one-month Treasury bill rates comes from Ken French's website.

To examine funds' factor loadings changes, we select the universe of active domestic diversified equity funds as the sample. We exclude fixed income funds, mixed equity and fixed income funds, international funds, sector funds, hedge or short style funds, index funds and ETFs. We also restrict attention to funds that have at least a certain minimum size. Following Elton, Gruber, and Blake (2001) and Pastor, Stambaugh, and Taylor (2015), we use data on fund asset size to drop small funds which have total net assets smaller than 15 million and thus have more noisy information.

All the data are aggregated to the fund level. Different share classes of one fund differ only in terms of the fee structure and minimum investment requirements. They share the same portfolio and so portfolio construction and style adjustments happen at the fund level. We therefore link funds using MFLINKS and calculate fund-level return as the asset-weighted return of all share classes of a fund.[7] We use fund name, index fund flag, ET (Exchange Traded) flag, and CRSP objective code from the oldest currently available share class of the fund in each period.

For each fund in our sample, we estimate quarterly four-factor (Carhart (1997)) loadings of funds to measure fund style and its change. Self-declared styles are not suited to capturing small style shifts, and are often inconsistent with actual styles because of misclassification (DiBartolomeo and Witkowski (1997), Bams, Otten, and Ramezanifar (2017), Cremers, Fulkerson, and Riley (2022)). To estimate factor loadings we assemble daily data on fund

[7]We use MFLINKS to aggregate up to the fund level, and we drop unmatched share classes.

net return,[8] factor portfolio returns, and one-month Treasury bill rates. Using daily return data allows us to estimate factor loadings at the quarterly frequency. We regress fund daily excess net returns over daily one-month Treasury bill rates on daily market excess returns, SMB, HML, and MOM. Since the daily fund net return data is available from September 1998, estimated loadings start from the last quarter of 1998.

When we compute the quarter-to-quarter changes in factor loadings, we subtract the respective loadings of the factor-neutral portfolios. Lettau, Ludvigson, and Manoel (2018) show that factor-neutral long-short portfolios do not have a factor loading of zero since the loading tends to tilt towards the more volatile side of the portfolio. For SMB, HML and MOM factors, we construct factor-neutral portfolios as long stocks above the median characteristic for each factor and short stocks below the median characteristic. Therefore, what defines a fund's style in one period and makes styles comparable across periods is not the distance from a fund's loading to zero but the distance from a fund's loading to the factor-neutral portfolio's loading. We make this adjustment for all loadings except the market loading. Market loadings are compared to one in all periods and thus used to calculate changes without adjustment.

It is useful to consider a specific example for illustration. The SMB loading of the Fidelity Equity Income Fund is -0.14 in the third quarter of 2002 and -0.15 in the fourth quarter of 2002, while the SMB-neutral portfolio's SMB loading decreases from 0.47 to 0.42 during the same period. The loading of the fund is below that of the neutral portfolio and thus tilts to the large style in both periods. However, in the second period, it moves closer to the neutral portfolio and invests less in the large style. This is true even though the fund's loading becomes slightly more negative.

Since specific directions in which fund managers might choose to change styles vary with market conditions, loadings changes in this study focus on magnitudes and do not account for directions or signs of changes. So, the final measure is the absolute value of the change.

[8]We use the terms "net return" and "after-fee return" interchangeably. Likewise, we use the term "before-fee return" interchangeably with "gross return."

We calculate fund flows in accordance with prior literature, and this calculation requires total net assets and monthly net return of a fund. Flow is defined as the change in total net assets not explained by the return: $flow_t = (TNA_t - TNA_{t-1} \times (1 + R_t))/TNA_{t-1}$, where TNA_t and TNA_{t-1} are respectively total net assets at the end of quarter t and quarter $t-1$, R_t is compounded net return in quarter t based on three monthly net returns in the quarter.

We compute four-factor alphas. In the regression, we include prior quarter alpha to control for the possible influence of return on fund flow (through the return-flow relation); in addition, prior alpha may also have a direct impact on style changes. The positive return-flow relation is found using raw return rank (Sirri and Tufano (1998)), (style-adjusted) four-factor alpha (Lynch and Musto (2003)), and one-factor alpha (Berk and Binsbergen (2015)). However, raw returns and one-factor alphas include SMB, HML and MOM loadings. Moreover, when investigating the relation between return and loadings changes, Chan, Chen, and Lakonishok (2002) use three-factor alpha, and Lynch and Musto (2003) use four-factor alpha; we also use four-factor alphas.[9]

In order to reduce the effect of outliers, each quarter we winsorize factor loadings, flows and alphas at the 1% and 99% levels. Finally, we use monthly total net returns in the past 12 months to measure return volatility.

1.2.2 Summary statistics

In order to be included in the analysis we require non-missing data for the fund flow, alpha, lagged alpha, next period absolute loadings change, and return volatility calculated as the standard deviation of monthly fund returns over the previous 12 months. Daily fund return data in CRSP is available starting in September 1998. The first quarter with estimates of factor loadings and alphas is the fourth quarter of 1998, and the first quarter in our sample is the second quarter of 1999, by which two quarter lagged alpha becomes available. The

[9]Given the results in Berk, Jonathan B., and Jules H. Van Binsbergen (2016) and Barber, Huang, and Odean (2016) that fund flows respond to Jensen's alpha rather than four-factor alphas and thus these are the alphas that managers may care about more, we have replicated our analysis with the CAPM alphas and found that the results are robust to this change.

final sample includes 3,874 funds from the second quarter of 1999 to the fourth quarter of 2021. Table 1.1 reports summary statistics for our main sample of diversified domestic equity active funds.

Average and median market beta are equal to 0.94 and 0.97 respectively. Funds have an average tilt toward small cap stocks, reflected in more extreme positive loadings on SMB; the median is equal to 0.05, while the mean is 0.19. Funds are neutral relative to the momentum and value/growth styles, reflected in average and median loadings that are close to zero. These values are consistent with the distribution of mutual fund factor loadings reported in Lettau, Ludvigson, and Manoel (2018). As for the time dimension, we observe that there is substantial variation in factor loadings quarter to quarter. We have checked the average factor loadings through time (unreported) and find that SMB and HML loadings decline, though adjusted loadings do not have a trend since the loadings on the factor-neutral SMB and HML portfolios also decline.

Absolute changes in factor loadings, which we measure as the absolute value of the difference in the adjusted factor loading from one quarter to the next, are largest for HML and smallest for MKT. Mean absolute changes lie between 0.08 to 0.15 and the median changes lie between 0.05 and 0.11. Since the absolute values are right-skewed, the 75th percentile values are much larger, and lie between 0.10 for market loadings and 0.20 for HML loadings. There is significant time variation in average absolute loadings changes. Figure 1.1 reports magnitudes of loadings changes for all four loadings over time. The average absolute loadings change decreases for all loadings. Throughout the sample, HML, SMB and MOM loadings changes are generally larger than MKT loadings changes (Wermers (2012) shows a similar result estimated from the portfolio holdings data). In our regression analysis on the determinants of loadings changes we therefore include time fixed effects to account for this variation.

The statistics for fund flows show that there are more occurrences of outflows than inflows, but in terms of magnitudes, outflows are, on average, smaller in magnitude than inflows. Outflows are also less variable than inflows. On average, the fund flow declines during the sample period, as shown in Figure 1.2, which plots average quarterly flows. For both outflows and inflows, the mean flows are larger in absolute value than the median flows, suggesting that the distribution of the absolute fund flows is right-skewed.

The median quarterly fund alpha is equal to -0.25%, which indicates that the value added by active fund management, to the extent that it is present, is smaller than the fees charged for more than half of the observations. The alpha distribution appears somewhat left-skewed. The distribution of fund size is very right-skewed. Median TNA is $316 million, while the mean is equal to almost $1.7 billion. Finally, the median fund in the sample has almost nine years of data, which amounts to a little less than half our total sample period.

1.3 Effect of prior flows and returns on style changes

In this section, we establish that funds change styles following extreme returns and fund flows.

1.3.1 Unconditional patterns: Graphical analysis

We start by analyzing the unconditional relationship between style changes and past fund flows and returns. We begin by sorting funds into 100 equal-sized groups by their fund flow in each quarter. For each group we then measure the average absolute value of the loadings change for each of the four factors over the following quarter. Figure 1.3 Panels A to D plots the average absolute loadings changes by fund flow percentile. The relation between loadings changes and past flows is U-shaped or V-shaped, with both larger outflows and larger inflows followed by larger changes in loading. We also note that the effects are comparable across factors, with the effect being slightly weaker for the market factor and not as strong for inflows for the momentum factor.

In our regression analysis we will capture the non-linear effect in three different ways, first, by assuming a U-shaped pattern with downward and upward sloping segments for more extreme flows and a flat segment for smaller absolute flows; second, by assuming a V-shaped pattern, where we assume a downward and an upward sloping segment; and third, assuming that both large outflows and large inflows are associated with larger style changes and estimating the average effect by including two dummy variables capturing large absolute flows.

We next repeat the same procedure but for alphas. Each quarter we sort funds into percentiles by their four-factor alphas in that quarter and then measure the average absolute loadings change over the next quarter. Figure 1.4 shows the plots. The pattern is very similar to the relationship between flows and style changes, though less noisy. As with flows, we note that the relationship is similar across factors, suggesting that it will be possible to examine factor loadings changes together. Figure 1.5 reports the results for the two-quarter-ahead loadings changes, and the pattern is again very similar. The results so far suggest that managers react to large past flows and returns by changing factor loadings.

1.3.2 Piecewise linear regressions

To capture the nonlinear relationship between loadings changes and past returns and fund flows shown in the figures, we run piecewise linear regressions. Specifically, fund flows and returns are each divided into large negative, intermediate and large positive segments. Each quarter, the bottom 25% of the distribution is classified as large outflow, the 25th to the 75th percentile is classified as intermediate level flow, and the top quartile is large inflow. We then choose a piecewise linear specification that connects the three linear parts of the model. We construct the same three segments for fund returns measured by four-factor alphas. In this way, fund flow, alpha and lagged alpha are each broken up into three segments: bottom quartile, middle 50%, and top quartile.

Table 1.2 presents the results of regressing the mean absolute loadings changes on past fund flows and returns as well as other controls. In all regression specifications, we include lagged average absolute loadings as a control variable because it is possible that loadings changes are at least partly driven by mean reversion.[10] We indeed find that in four out of the five specifications there is a significant positive coefficient on the average absolute loadings in the prior quarter.

Consistent with the pattern observed in Figure 1.3, Table 1.2 shows a large negative coefficient for larger outflows and a large positive coefficient for large inflows, this means that both large outflows and large inflows in the current quarter are followed by a larger style change in the next quarter. The effect of lagged intermediate flow is much smaller and indistinguishable from zero when all controls are included.[11]

In specifications (2)–(5), we add more explanatory variables: fund's four-factor alphas, the alphas lagged by one quarter, and return volatility. Lagged alphas may have a direct incremental effect on the change in loadings two quarters later. Additionally, lagged alphas may affect future loadings changes through their effect on fund flows in the following quarter. If this is the case, the unconditional effect of flows on style changes identified in the figures and in the first regression specification may partly be driven by the well-documented return-flow relationship. Return volatility is measured as the standard deviation of a fund's monthly returns over the previous 12 months. Similar to the specification for flows, we include three linear segments for alphas and lagged alphas: large negative, large positive and intermediate segments.

The results show that large negative alphas are followed by large loadings changes (consistent with Chan, Chen, and Lakonishok (2002) and Lynch and Musto (2003)), and the magnitude of the loadings change increases with the magnitude of the underperformance (the coefficient on large negative alpha percentile is negative and highly statistically signif-

[10] A factor-neutral fund will have adjusted HML, SMB, and MOM loadings of zero and a MKT loading of one; hence, large absolute loadings measured in the previous quarter may result in large loadings changes in the next quarter due to mean reversion. Such mean reversion could partly be driven by noisy measurement of loadings changes.

[11] Since fund flows are autocorrelated, and the change in style may be instead responding to the current quarter's flows, we have also including the current quarter's fund flow as an additional control for robustness and obtained very similar results, though the coefficient on past fund flows is slightly smaller.

icant). However, well-performing funds change styles as well, and more so the higher the alpha. To the best of our knowledge, we are the first to document style changes for outperforming funds. It can be explained by either factor timing or unconstrained stock selection, which involves replacing stocks whose prices already adjusted to their fair values with any undervalued stocks, irrespective of their characteristics.

The additional control variables are all highly significant. With the inclusion of alphas and lagged alphas, the effect of fund flows is cut almost in half, though it remains highly statistically and economically significant. The effect of fund flow on style change, therefore, appears to be partly driven by the return-flow relationship, but an important effect remains once we control for returns, indicating that funds react both to returns and flows. Return volatility is a large and highly significant predictor of future loadings changes. The effect may work through two channels: more volatile returns may lead to higher loadings changes, and volatility may increase noise of measured fund loadings and therefore loadings changes.

The pattern in the coefficients on fund alphas is similar to the unconditional results shown in Figures 1.4 and 1.5. Coefficients for large negative alpha and lagged large negative alpha indicate that a negative return of larger magnitude leads to a larger style change; the same is true for large positive alpha and lagged large positive alpha. Intermediate percentiles of alpha do not result in any change in style.[12] Coefficients for lagged alpha show that funds also consider performance two quarters ago when changing styles.

The economic magnitudes of the estimated coefficients on alphas are large. Taken together, the magnitude of the loadings changes in response to the returns in the prior two quarters are consequential: all else equal, compared to a fund in the 75th percentile of the alpha distribution, a fund whose alpha is in the 100th percentile of the distribution will shift its factor loadings by 0.063 two quarters out ([13.4bp+11.8bp]$\times$25, based on the estimates in the regression specification (2)). If a particular factor risk premium is, say, 10% per year, then

[12]In a previous version of the paper we included four segments – all quartiles of flow and return. The (unreported) results confirm that coefficients for intermediate percentiles of fund flow and return are not associated with statistical significance when explaining style changes.

the shift of this magnitude would alter the annual expected return by $0.063 \times 10\% = 0.63\%$, which is on the order of magnitude of fees charged by actively managed funds. The result that managers change styles following good performance, to the best of our knowledge, is new to the literature, and the change in fund styles that follows good performance is difficult to attribute to agency reasons.

1.3.2.1 Additional controls: Time and fund fixed effects

Investors' style preferences and common investment strategies may change over time. For example, there could be large outflows as investors change from active to index funds. There may be important aggregate changes in styles (Figure 1.1) that can be related to time variation in flows resulting from a general growth or decline of all active funds in the sample (Figure 1.2). The aggregate relation between returns, flows, and style changes may be particularly strong in periods when actively managed funds experience low returns. Moreover, fund flows may have seasonal patterns, and may conicide with the times when funds rebalance and change styles. We control for the possibility of such effects by adding quarterly-frequency time fixed effects; the fixed effects control for an overall trend in aggregate flows and shifts in styles, as well as seasonality in flows and fund rebalancing activities, and other time patterns of returns, fund flows and investment styles. The specification with time fixed effects is presented in column (3). The results show that the effects of flows and returns on style changes remain unchanged and statistically significant compared with column (2).

It is also possible that some funds are more active than others, and the more active funds (relative to the index) may both exhibit large style changes and experience more extreme returns and fund flows. These effects are already controlled for by including both prior absolute style level and volatility. However, since funds' being close to or deviating from the index is a relatively stable strategy over time for each fund, an additional way to control for it is to include fund fixed effects.

Results with fund fixed effects are reported in column (4). Effects are estimated of within-fund variation in style changes, returns and flows. The results indicate that there is indeed important variation across funds in our three main variables not captured by the other controls. Including fund fixed effects results in much smaller coefficients on returns, which are cut by more than half; coefficients on fund flows are also reduced, especially on outflows. Nevertheless, the effects of fund flows and returns on subsequent style changes remain significant. Finally, in column (5) we include both fund fixed effects and time fixed effects. The results are slightly smaller than those with fund fixed effects only in column (4) but remain significant.

We note that the strong relation between positive returns and style changes documented here is different from Wermers (2012), who shows a contemporaneous positive relation between fund manager career-average stock-picking return and style change. The panel regression in this paper relates past returns to future style changes, and also controls for fund and time fixed effects. While the return in Wermers (2012) is the average level for a fund manager, in the specifications with fund fixed effects, the return in this panel regression is the deviation from the average. The interpretation is that after fund managers experience unexpected large return deviations from the average return, they react by changing the fund style.

1.3.3 Robustness tests

In this subsection, we consider a number of alternative specifications and variable definitions used in Table 1.2 and find that the results are robust to these changes. We begin by investigating loadings changes separately on each of the four factors. We obtain largely similar results to those in the main table that predicts the *average* absolute loadings change in the next quarter: Extreme returns and fund flows lead to large loadings changes across all four factors. The results are discussed in the Appendix section A.II and reported in the Appendix tables A1 through A4.

We next choose different specifications to uncover the non-linear effects of returns and fund flows on the next quarter's style change. So far, we have used percentile ranks instead of actual returns and fund flows to reduce noise; very large flows and returns can be quite extreme, even after winsorization. Using the percentile rank reduces that variability to ensure that results are not driven by it. However, it is useful to check whether or not the results shown in Table 1.2 are robust to using actual values of fund flow and return instead. We additionally move from a three-segment to a two-segment piecewise linear specification for returns and fund flows: We estimate a V-shaped specification with only two linear pieces for returns and fund flows. These results are discussed in the Appendix section A.III. The main regression results are presented in the Appendix Table A5, and the results for each of the four factors are presented in the Appendix Tables A6 through A9. Consistent with the previous results, this specification shows V-shaped effects—both negative and positive alphas and negative and positive fund flows result in a large change in absolute loadings. Moreover, these results hold for the absolute loadings changes in each of the four factors.

Yet another way to identify the non-linear effects of fund flows and returns on future style changes is to include dummies for large outflows and large inflows (top and bottom fund flow quartiles) and for large negative and large positive alphas and lagged alphas (top and bottom alpha quartiles). This specification also uncovers positive significant effects of these dummies on future absolute loadings changes.[13]

One may be concerned that our results are related to the liquidity of the stocks held in the portfolio. For example, managers may be responding to negative flows by selling off the more liquid stocks, and the factor loadings may be altered if these stocks have different characteristics than the rest of the portfolio holdings. To check this, we exclude funds that hold small stocks (identified as funds in the top 30% of the SMB betas). The coefficients on the lagged flows become somewhat lower, but the coefficients on past alphas remain very similar in magnitude.[14]

Since there may be mean-reversion in factor loadings, we also consider a specification

[13]To save space these results are not reported but are available upon request.
[14]These results are available upon request.

with the lagged absolute mean loadings change as an additional explanatory variable. Since the lagged dependent variable cannot be included in the specification with fund fixed effects (see, e.g., Angrist and Pischke (2009)), we include it in the specifications with and without time fixed effects but no fund fixed effects. The coefficient on the lagged loadings change is positive and significant, but the coefficients on past extreme fund flows and alphas remain significant. These results are reported in the Appendix Table A10.

Finally, we analyze separately fund style changes earlier and later in the year. If factor loadings changes are driven primarily by agency issues, the effect should be stronger later in the year: Brown, Harlow, and Starks (1996) show that underperformance by July already leads managers to increase the riskiness of their portfolios for the rest of the year, and Chevalier and Ellison (1997) show that underperforming managers increase the riskiness of their portfolios in the fourth quarter. When we focus separately on loadings changes in quarters 1 & 2 and quarters 3 & 4, or quarters 1 through 3 and quarter 4, we obtain very similar coefficients on past flows and returns for all subsamples. The results are reported in the Appendix Tables A11 and A12, respectively.

1.4 Loadings Changes, Trading, and Skill

Having documented that managers change fund style as a consequence not only of bad but also of good performance, we next show that style changes are the result of deliberate trading decisions and not passive style drifts. We then investigate whether or not style changes can influence future fund performance.

1.4.1 Changes in factor loadings and trading activity

A concern with our analysis of loadings changes might be that a fund's factor loadings can change mechanically as a result of individual assets held in the portfolio changing their factor loadings over time. While this mechanism is unlikely to result in significant loadings changes when aggregated to the fund level, we nevertheless perform a test to ensure that factor loadings changes ensue from deliberate trading decisions of the fund manager. For this test, we use the annual turnover measure provided in the CRSP Mutual Fund database, which is calculated at the end of each year t for each fund i, as the minimum of the fund's total purchases and sales over year t scaled by the fund's average TNA in year t:

$$FundTurnover_{i,t} = \frac{min(buys_{i,t}, sells_{i,t})}{AvgTNA_{i,t}}. \tag{1.1}$$

As pointed out by Pastor, Lubos, Robert F Stambaugh, and Lucian A Taylor (2017), this definition of turnover, used by the Securities and Exchange Commission, largely excludes turnover arising from persistent inflows and outflows to and from the fund and rather reflects the fund's active decisions to change portfolio holdings.

To check whether larger factor loadings changes are associated with a higher portfolio turnover, we perform the following test. At the end of each year t, we calculate average portfolio loadings change over the past four quarters. We then sort funds into quintile portfolios based on this average loadings change measure and calculate the average fund turnover for each portfolio, as well as the difference between the high- and low-loadings-change portfolios.

The results are presented in Table 1.3. The table shows that the average fund turnover increases monotonically with the average loadings change, from 0.63 for the lowest loadings-change fund quintile to 0.97 in the highest loadings-change fund quintile, and the difference in turnover of 0.34 between the extreme quintiles is highly statistically significant, with a t-statistic of 9.69. This result suggests that loadings changes reflect managers deliberately replacing some of their portfolio holdings with others that have systematically different factor loadings. This result is consistent with Wermers (2012), who also finds that style drift largely results from managers' trading decisions.

1.4.2 Changes in factor loadings and future performance

The evidence so far shows that some managers respond to extreme conditions by changing factor loadings of their portfolios. We now ask if these changes can help funds improve future performance, or perhaps destroy value.

1.4.2.1 New measure: 'Tactical investment skill'

In principle, some flexibility with fund loadings can help improve performance. Some recent studies show that the factor premia are not constant through time and may be forecastable,[15] and that factor timing strategies are possible (e.g., Levis and Tessaromatis (2004), Haddad, Kozak, and Santosh (2020), and Ilmanen, Israel, Moskowitz, Thapar, and Lee (2021)). Hence, skilled managers may improve fund performance by changing factor loadings in response to market conditions. Managers may also not engage in an outright factor timing strategy but rather achieve favorable loadings changes through unconstrained stock picking decisions, i.e., buying stocks with good prospects and selling stocks with poor prospects while not restricting the trades to maintain constant portfolio factor loadings. In contrast, style changes implemented for agency or behavioral reasons may be detrimental to fund performance because these changes will not increase expected returns but surely destroy value through trading costs.

We propose a new measure of a manager's skill based on their track record of achieving higher returns through loadings changes. We hypothesize that some fund managers may be more skilled than others at unconstrained stock selection that alters portfolio loadings or factor timing while other managers may have negative "skill" if they trade for agency or behavioral reasons. We measure what we refer to as a manager's "tactical investment skill" by running the following rolling regression. For each fund i in each quarter τ, we use a 5-year quarterly-frequency trailing window $[\tau - 19, \tau]$ to regress the fund's excess return in current

[15] See, e.g., Daniel and Moskowitz (2016), Cohen, Polk, and Vuolteenaho (2003), Polk, Thompson, and Vuolteenaho (2006), Pettenuzzo and Timmermann (2011), and Polk, Haghbin, and De Longis (2020).

quarter t on the absolute loadings change, $|\Delta Loadings|$, in the previous quarter, $t-1$:

$$ExcessRet_{i,t}^{\tau} = \alpha_i^{\tau} + \beta_i^{\tau}|\Delta Loadings_{i,t-1}^{\tau}| + \epsilon_{i,t}^{\tau} \quad (1.2)$$

The estimated regression coefficient $\hat{\beta}_i^{\tau}$ is our measure of fund i's manager's "tactical investment skill" in quarter τ. A high estimate of $\hat{\beta}_i^{\tau}$ would thus indicate high skill and a low estimate low skill.

Summary statistics for tactical investment skill, winsorized at the 1% level, are reported in Table 1.4. Note that, ex ante, it is possible that all managers have positive or negative tactical investment skill, implying that loadings changes could always be harmful or helpful. Instead, we find a split, consistent with the idea that loadings changes have many reasons, some resulting in higher returns, some in lower returns. The table shows that the mean skill is slightly negative, while the median skill is equal to zero. Managers at the 25% percentile of the skill distribution destroy value with their loadings changes (their skill measure is negative), while managers at the 75th percentile of the skill distribution add value (their skill measure is positive).

To get a sense of economic magnitude, we consider a manager with high skill who also engages in high loadings changes. A one standard deviation increase in skill, 0.49, multiplied by the average standard deviation of quarterly loadings changes, 5%, results in an estimated in-sample outperformance of 2.5% per quarter. Moreover, skill is slightly left skewed. We have thus established that loadings changes can be beneficial and increase returns, but they can also lead to lower returns. However, if this measure of skill is to be useful as a predictor of future returns, we need to establish a relationship with future fund performance.

1.4.2.2 Do skilled managers earn higher returns? Predicting fund performance

To check whether managers who have exhibited tactical investment skill outperform their low-skill peers in the future, we perform the following test. In each month, we sort all funds into quintiles based on the manager's tactical investment skill measured as of the most recent quarter-end: bottom 20% (low-skill funds) up to top 20% (high-skilled funds). We then calculate the average before-fee monthly fund portfolio return and the average return differential between the high- and low-skill funds.[16] The average annualized fund returns, return differentials, and their four-factor alphas are reported in Table 1.5.

The table shows that the average excess returns and the corresponding four-factor alphas indeed monotonically increase in our skill measure. The average annualized excess return earned by the funds in the bottom tactical skill quintile is 9.33%, and is equal to 10.91% for the funds in the top quintile. The high-skill minus low-skill raw return differential is 1.58% (t-statistic$=2.75$). This magnitude of outperformance is economically meaningful, it is higher than a typical expense ratio for an actively managed fund. Based on the four-factor alpha, the table shows that low-skill managers appear to destroy investor value (the four-factor alpha is -0.83%, with a corresponding t-stat of -1.62), either due to agency reasons or manager irrationality, and should be avoided. The four-factor alpha of the return differential is 1.09% (t-statistic$=2.08$). The positive and significant four-factor alpha suggests that the high-skill managers' ability to outperform their low-skill peers through factor loadings changes is not entirely explained by factor timing, which would have resulted in a low level of alpha.

The results are robust to various other choices for the skill sorting breakpoints. When using after-fee alphas (see Appendix table A13), remarkably, none of the alphas are positive, and the low-skilled funds earn significantly negative alphas. However, the outperformance of the high-skill relative to the low-skill managers is similar in magnitude, implying that high-skill managers do not systematically charge higher fees than low-skill managers. As the before-fee results indicate, some managers tend to create some value before fees; however, net of fees, alphas are negative. This pattern becomes more pronounced when, following Cremers, Petajisto, and Zitzewitz (2012), we use tradable commercial benchmark indices,[17] composed

[16] We calculate before-fee fund returns by adding the expense ratio to the post-fee return.

[17] We recalculate the alphas in Table A14 using S&P500 index for the market factor, the return on the Russell 2000 index minus the return on the S&P 500 index for the size factor, the return on the Russell 3000 value index minus the return on the Russell 3000 growth index for the value factors, and the Carhart (1997)

only of U.S. based stocks, and used by active mutual funds as benchmarks in place of the Fama-French factors (See appendix Table A14). With this adjustment, high-skill funds earn a before-fee alpha of 0.69%, though the point estimate is not quite statistically significant at conventional levels (t-stat of 1.37), while low-skilled managers earn a statistically insignificant but negative alpha of -0.40.

1.4.2.3 Conditioning on the change in factor loadings

Having shown that skilled managers can increase future returns by changing factor loadings, we further investigate whether the magnitude of future outperformance is related to the magnitude of loadings changes. That is, do managers skilled in using loadings changes to increase returns do better at times when they are changing loadings by more?

For this analysis, we perform an independent double sort. In each month, we form portfolios of mutual funds sorting on loadings changes and skill. We sort funds into high-medium- and low-skill groups, using our tactical skill measure, estimated as of the most recent quarter. We use a 20-60-20 split, so that results are comparable to Table 1.5. We also sort funds into bottom, middle, and top groups based on the average of the absolute four loadings changes in the most recent quarter. We then calculate average monthly returns for each fund portfolio, monthly return differentials between the high- and low-skill portfolios for the extreme loadings-change groups, as well as the corresponding four-factor alphas.

The results are reported in Table 1.6. There is a clear split between low and high loadings changes, indicating that higher-skill matters more when loadings changes are higher. For the high loadings change group, fund returns and alphas increase monotonically with skill. The return differentials, between the high- and low-skill fund portfolios, and the corresponding four-factor alphas, are positive and statistically significant. Notably both are also higher than the single-sort return and alpha differentials reported in Table 1.5, though there is also slightly higher noise reflected in similar t-statistics. In contrast, the relationship between skill

momentum factor.

and return is much weaker for funds with low loadings changes—the pattern is no longer monotonic. High-skill funds still outperform low-skill funds but the difference is small and not statistically significant. These results are also present in the robustness checks, in which we consider net returns instead of gross returns (reported in Appendix Table A15) and when we compute gross return alphas using tradable commercial benchmark indices proposed by Cremers, Petajisto, and Zitzewitz (2012) (reported in Appendix Table A16).

We perform a number of additional robustness checks. First, we perform a conditional double sort, where we first sort on loadings changes and then skill. We find similar results (Table A17). We also perform a conditional double sort with more extreme bins. Instead of a 20-60-20 split we use a 10-80-10 split. This results in much smaller portfolios of funds in the extreme groups. However, we do find that the effect of skill is stronger there—when both the skill level is higher and the loadings changes are larger. Specifically, for the high-loadings-change group, the magnitude of the skill-induced excess return differential is 4.13% per year, with a corresponding t-statistic of 3.65. The annualized four factor alpha is equal to 3.26% with a t-statistic of 3.01. These magnitudes of outperformance are roughly twice as large compared to those found in the single sort on skill. This is most likely driven by the more extreme sort performed. Using index fund benchmarks following Cremers, Petajisto, and Zitzewitz (2012) (Table A18) patterns are similar. One notable difference is that high-skill funds now outperform the benchmark during high-loadings change quarters. The alpha is equal to 2.15% and has a t-stat of 1.85.

We also perform a less extreme (independent) sort using 30-40-30 breakpoints (unreported) and find that our results continue to be robust. Most likely because of lower levels of return volatility, we find slightly higher significance of the return differentials. The high-minus-low skill return differential for the high-loadings-change group is 1.68% per year (t-statistic= 3.18), and its four-factor alpha is 1.27% (t-statistic= 2.62); results using index benchmark alphas are similar.

In sum, the results in this section show that the tactical investment skill, which captures a manager's track record of increasing returns through style changes, has a predictive ability for future performance differences between the high- and low-skilled managers. Supporting this interpretation, the effect of skill on future returns is stronger following periods of large loadings changes. Differences in performance are economically large and exceed a typical expense ratio charged by actively managed funds.

Our estimates of the return magnitudes and the corresponding statistical significance levels are similar to those reported in other papers that predict mutual fund returns based on the papers' respective measures of manager skill by sorting funds into portfolios based on the skill measure. Because funds are already well diversified, even small return differentials tend to be highly statistically significant. For example, Cremers and Petajisto (2009) develop a measure of a manager's "activeness" based on the deviation of a fund's holdings from its benchmark portfolio, which the authors label "active share," and then sort funds into quintiles based on this measure. They show that over the 1990–2003 sample period the annualized four-factor alpha of the return differential between the high- and low-active-share quintiles is 1.14% (t-statistic= 2.53). Amihud and Goyenko (2013) argue that funds with a low R^2 obtained from regressing past fund returns on benchmark factors may be more skilled at individual stock selection and then show that over the 1990—2010 period, when sorted into quintiles based on the return regression R^2, funds in the low quintile outperform funds in the high quintile by 2.05% per year (t-statistic= 2.68). Finally, Jiang and Verardo (2018) argue that mutual fund herding in trades reveals low skill and form decile portfolios of mutual funds based on their herding measure calculated in the past quarter. They find that over the 1990 to 2009 sample period the annualized four-factor alpha of the return differential between the bottom and top herding deciles is 1.92% (t-statistic= 2.93).

1.5 Conclusion

This study shows that both prior returns and prior fund flows motivate fund managers to change styles. We measure style changes as the average absolute value of loadings changes across the four Fama and French (1993) and Carhart (1997) factors. We find that both low and high past returns and fund flows lead managers to change fund styles in the future. Changes in fund styles result from active trading decisions rather than from a passive style drift. One potential explanation of this behavior could be agency problems, whereby managers change fund styles as a result of poor past performance, in order to catch up with other managers and to attract fund flows. We hypothesise that, in addition, a subset of managers may be trying to achieve higher returns through an unconstrained stock selection or factor timing.

We explore if and to what extent managers can indeed improve future performance by changing fund styles. The answer depends on whether a manager has demonstrated a prior track record of achieving higher returns by altering factor loadings. We first show that some managers have a track record of achieving higher returns after higher factor loadings changes, while others have lower returns following factor loadings changes. This implies that loadings changes can have quite different effects on performance. We then show that managers who were able to improve fund returns through factor loadings changes—those with what we call a "tactical investment skill"—continue to outperform managers who reduced returns when engaging in style changes. In a quintile sort, the skilled managers outperform unskilled managers by 1.58% per year, on average, and this magnitude is highly statistically significant and exceeds most active funds' expense ratios. The outperformance cannot be attributed purely to the factor timing ability since it is associated with a positive and significant four-factor alpha. The results, which are based on before-fee returns, indicate that there is a clear spread in returns between high-skill and low-skill managers, and a return spread of a similar magnitude is present for after-fee returns. Consistent with the idea of unencumbered managers being better able to generate value, we find that the outperformance of high-skill managers is particularly pronounced following quarters with large loadings changes. We leave it to future work to identify the origins of the "tactical investment skill."

Figures

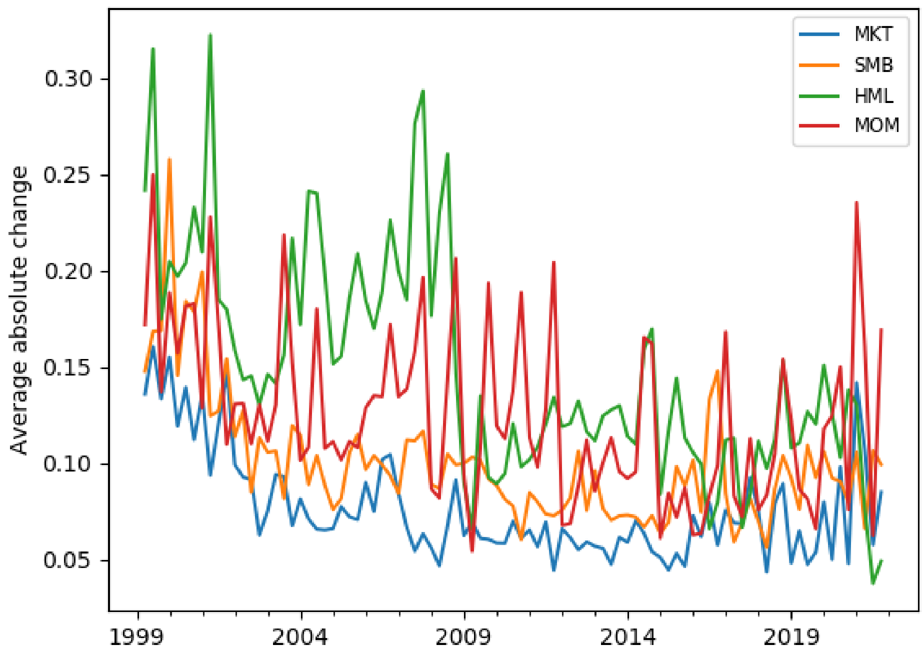

Figure 1.1: Average absolute changes in loadings over time

In each quarter and for each factor loading, all funds' loadings are averaged. MKT is the market loading. SMB, HML and MOM loadings are benchmark adjusted. Specifically, benchmark-adjusted SMB is the SMB loading of a fund minus that of the portfolio $(S+B)/2$ in each quarter. Benchmark-adjusted HML is the HML loading of a fund minus that of the portfolio $(H+L)/2$ in each quarter. Benchmark-adjusted MOM is the MOM loading of a fund minus that of the portfolio $(HiPrior+LoPrior)/2$ in each quarter.

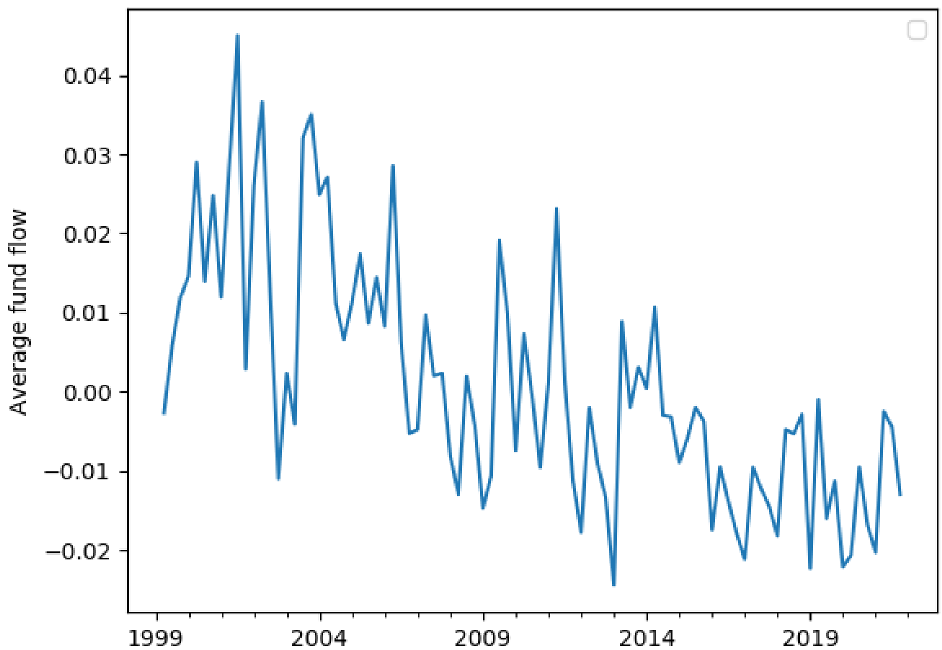

Figure 1.2: Average fund flow over time

This figure plots quarterly average fund flows from 1999 Q2 to 2021 Q4.

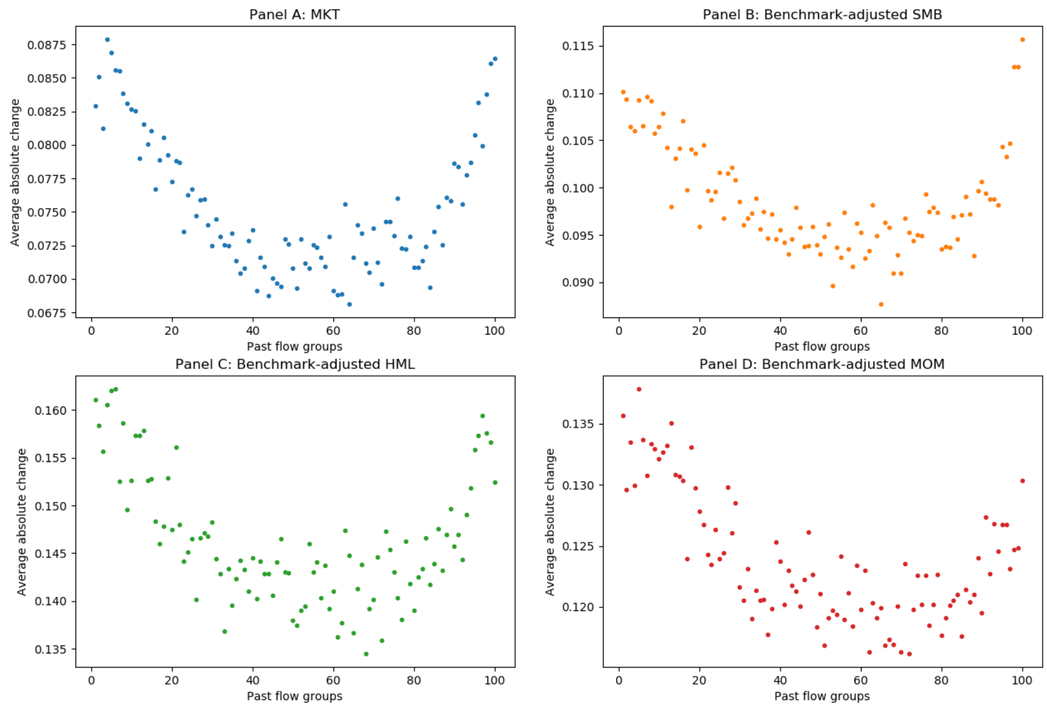

Figure 1.3: Absolute loadings change and past fund flow.

Each quarter, funds are classified into 100 equal-sized groups based on flow in the last quarter. For each of the 100 groups, average absolute loading changes are calculated.

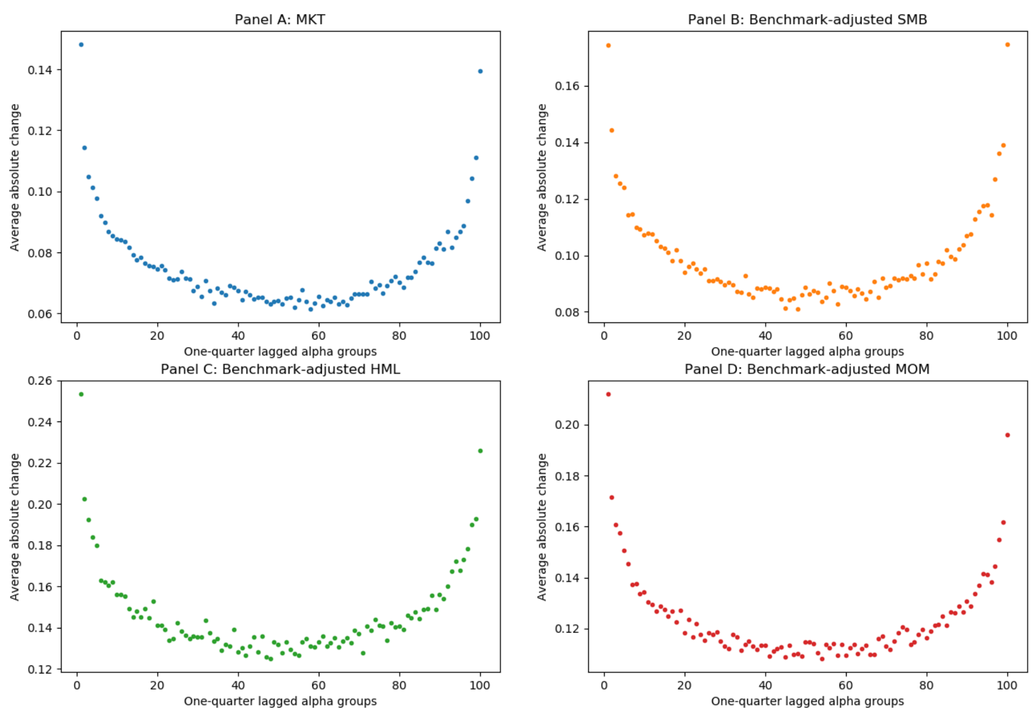

Figure 1.4: Absolute loadings change and one-quarter lagged alpha

Each quarter, funds are classified into 100 equal-sized groups based on alpha in the last quarter. For each of the 100 groups, average absolute loading changes are calculated.

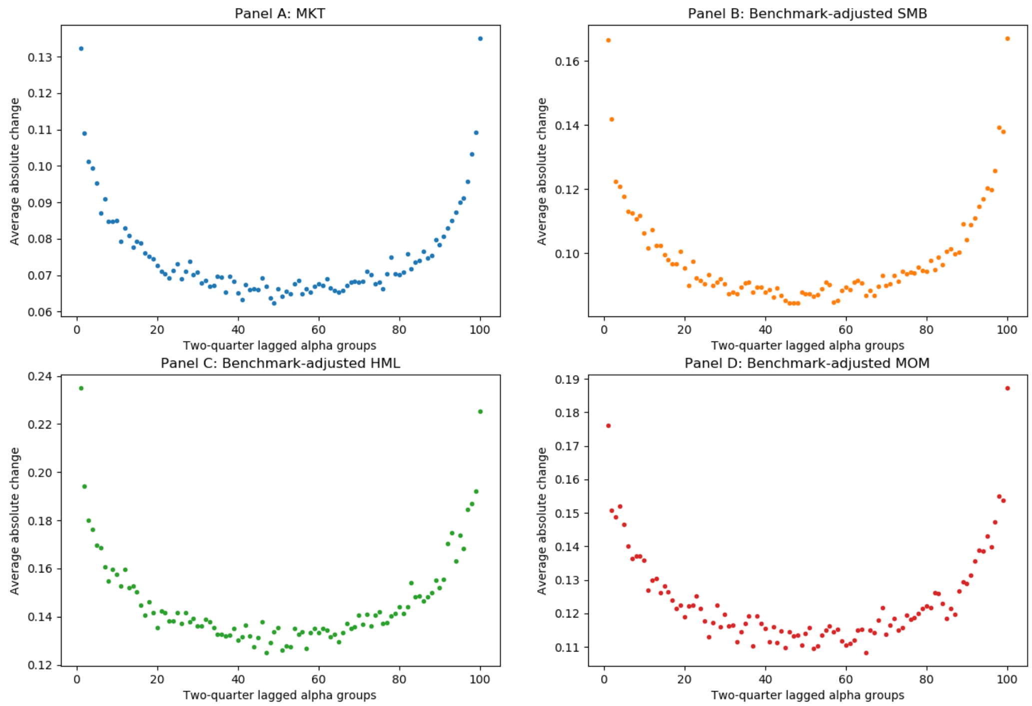

Figure 1.5: Absolute loadings change and two-quarter lagged alpha

Each quarter, funds are classified into 100 equal-sized groups based on two-quarter lagged alpha. For each of the 100 groups, average absolute loading changes are calculated.

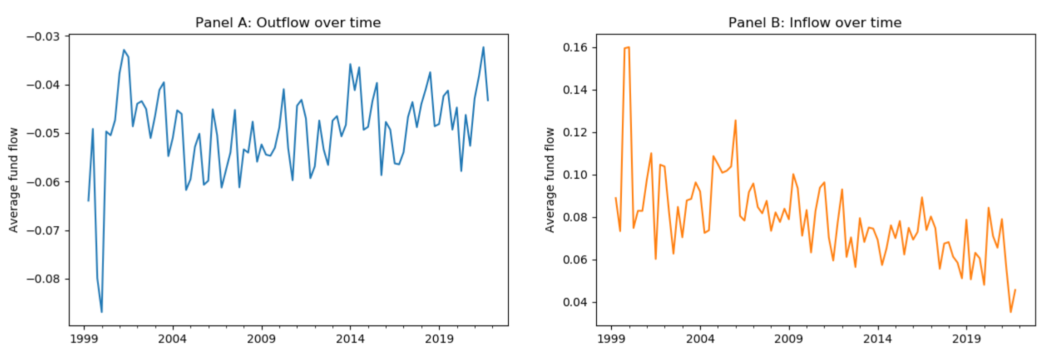

Figure 1.6: Fund outflow and inflow over time

In each quarter, the average outflow and inflow are calculated and shown.

Tables

Table 1.1: Summary statistics

	Count	Mean	Std.	25%	50%	75%
MKT loading	155,624	0.94	0.17	0.88	0.97	1.04
SMB loading	155,624	0.19	0.35	-0.07	0.05	0.43
HML loading	155,624	0.04	0.28	-0.12	0.04	0.22
MOM loading	155,624	0.02	0.19	-0.08	0.01	0.11
$\|\Delta$ adj. MKT loading$\|$	155,624	0.08	0.08	0.02	0.05	0.10
$\|\Delta$ adj. SMB loading$\|$	155,624	0.10	0.10	0.03	0.07	0.13
$\|\Delta$ adj. HML loading$\|$	155,624	0.15	0.14	0.05	0.11	0.20
$\|\Delta$ adj. MOM loading$\|$	155,624	0.12	0.11	0.04	0.09	0.17
Fund Flow	155,624	0.05%	10.57%	-4.21%	-1.49%	2.18%
Outflow	98,075	-4.91%	5.20%	-6.02%	-3.35%	-1.76%
Inflow	57,549	8.49%	11.95%	1.54%	4.22%	10.12%
Alpha	155,624	-0.29%	2.72%	-1.59%	-0.25%	1.03%
Negative alpha	86,226	-1.98%	1.97%	-2.62%	-1.41%	-0.65%
Positive alpha	69,398	1.80%	1.97%	0.54%	1.22%	2.36%
Total net assets ($ mil.)	155,624	1,741	6,553	97	316	1,127
# quarter per fund	3,874	40	29	16	34	63

This table reports summary statistics of quarterly factor loadings, loadings changes between two quarters, flow, alpha, asset size, and number of quarters since a fund entering the sample. The sample includes 3,874 funds from 1999 Q2 to 2021 Q4. Factor loadings and alpha are estimated from Carhart 4-factor model using daily fund return data in each quarter. Quarterly fund flow is defined as $\textit{fund flow}_t = (TNA_t - TNA_{t-1} \times (1 + R_t))/TNA_{t-1}$, where TNA_t and TNA_{t-1} are total net assets at the end of quarter t and quarter $t-1$, respectively, R_t is the compounded net return in quarter t based on the three monthly net returns in the quarter. Absolute changes in factor loadings are calculated based on factor loadings adjusted for the respective loading of factor-neutral portfolios. A fund enters the sample if it has data available in the prior three quarters.

Table 1.2: Regressions of average of absolute changes in four loadings on three segments of percentiles of flows and returns

	(1)	(2)	(3)	(4)	(5)
Large outflow percentile	-5.77***	-2.92***	-2.29***	-1.40***	-1.08***
	(-8.99)	(-5.93)	(-5.34)	(-3.22)	(-2.98)
Intermediate flow percentile	-0.90***	-0.56***	-0.50**	0.81***	-0.22
	(-3.80)	(-2.83)	(-2.59)	(3.19)	(-1.15)
Large inflow percentile	5.73***	3.61***	3.49***	2.88***	1.15***
	(8.20)	(7.20)	(8.08)	(5.40)	(3.06)
Large neg. alpha percentile		-15.88***	-14.34***	-6.64***	-6.85***
		(-15.26)	(-14.66)	(-8.51)	(-8.40)
Intermediate alpha percentile		0.00	0.12	0.15	0.08
		(-0.00)	(0.42)	(0.55)	(0.31)
Large pos. alpha percentile		13.36***	11.53***	5.23***	5.07***
		(15.25)	(14.92)	(7.44)	(7.52)
Lagged large neg. alpha percentile		-12.10***	-10.51***	-3.24***	-3.29***
		(-12.80)	(-12.14)	(-4.44)	(-4.62)
Lagged intermediate alpha percentile		0.00	0.10	0.14	0.06
		(-0.01)	(0.37)	(0.56)	(0.25)
Lagged large pos. alpha percentile		11.81***	9.91***	3.41***	3.36***
		(13.94)	(15.37)	(5.29)	(5.71)
Average abs. loading	8.49***	3.81**	0.40	5.62***	5.15***
	(4.07)	(2.72)	(0.39)	(3.01)	(3.44)
Return volatility		65.23***	129.35***	30.88**	91.27***
		(4.02)	(12.18)	(2.20)	(8.30)
Intercept	7.62***	12.11***	10.46***	8.41***	6.39***
	(7.12)	(10.65)	(11.05)	(6.83)	(5.44)
Fund fixed effect	NO	NO	NO	YES	YES
Time fixed effect	NO	NO	YES	NO	YES
Obs.	155,624	155,624	155,624	155,624	155,624
R2	0.02	0.12	0.31	0.29	0.42

The dependent variable is the average absolute change in adjusted factor loadings between quarter $t+1$ and quarter t that is averaged across the four factors. The loadings are estimated every quarter and the SMB/HML/MOM loadings are adjusted for the loadings of the respective factor-neutral portfolios. *Large outflow percentile* is $min(Flow\ percentile, 0.25)$, *Intermediate flow percentile* is $min(Flow\ percentile - Large\ outflow\ percentile, 0.5)$, *Large inflow percentile* is $(Flow\ percentile - Large\ outflow\ percentile - Intermediate\ flow\ percentile)$. Each quarter, the percentiles of alpha and lagged alpha are similarly split into three segments connected at 0.25 and 0.75. Return volatility is the standard deviation of monthly fund returns in the past 12 months. Abs. loading is the average of absolute value of adjusted loadings on MKT, SMB, HML and MOM factors. All independent variables are calculated in quarter t, and lagged alpha is calculated in quarter $t-1$. The sample contains 3,874 funds from 1999Q3 to 2021Q4. t-statistics are clustered in two dimensions: fund and time. *, ** and *** indicate significance levels at 10%, 5% and 1%, respectively.

Table 1.3: Loadings change and turnover

Loadings change	Turnover
1 (low)	0.63
2	0.64
3	0.68
4	0.73
5 (high)	0.97
5 (high) - 1 (low)	0.34***
t-statistic	(9.69)

Mutual funds are sorted into quintile groups based on the average of loadings changes in the four quarters ending at each fiscal year end. Loading change is measured by average absolute loading changes across MKT, SMB, HML and MOM. For each of the five quintiles in each year, mutual funds' annual turnovers in the same year are averaged.

Table 1.4: Summary statistics on the tactical investment skill measure

Mean	-0.05
Median	0.00
25th percentile	-0.31
75th percentile	0.25
St. Dev.	0.49
Skewness	-0.43

This table presents summary statistics on the tactical investment skill measure. Tactical investment skill is estimated in every quarter for each actively managed mutual fund by regressing the excess return earned by the fund in quarter t on the average absolute loadings change over MKT, SMB, HML and MOM factor loadings in quarter $t-1$ over a 5-year rolling regression window, as described in equation 1.2 in the text. The skill measure is winsorized at the 1% level.

Table 1.5: Before-fee returns of portfolios sorted on skill

Skill quintile	Average skill measure	Excess return	4-factor alpha
1 (low)	-0.65	9.33**	-0.83
		(2.54)	(-1.62)
2	-0.25	10.01***	-0.13
		(2.73)	(-0.21)
3	-0.04	10.13***	-0.09
		(2.78)	(-0.19)
4	0.15	10.64***	0.21
		(2.86)	(0.37)
5 (high)	0.49	10.91***	0.25
		(2.87)	(0.51)
5 (high) - 1 (low)	1.14	1.58***	1.09**
		(2.75)	(2.08)

Every month, all actively managed equity mutual funds are sorted into quintiles based on their tactical investment skill, which is estimated as of the most recent quarter-end with rolling 5-year regressions of quarterly excess return on the average absolute change in factor loadings across MKT, SMB, HML and MOM factors. Before-fee monthly returns are then averaged across funds in each quintile, and the average annualized excess returns, their four-factor alphas are reported in the table in per cent, and the corresponding t-statistics are reported in parentheses. *, **, and *** indicate significance levels are at 10%, 5% and 1%, respectively.

Table 1.6: Portfolios independently sorted on loading change activity and skill, before-fee

		Skill			
Loadings change		Low	Middle	High	High - Low
low	Ex. Ret.	9.66***	9.56***	10.34***	0.69
		(2.70)	(2.70)	(2.82)	(0.70)
	Alpha	-0.11	-0.38	0.17	0.28
		(-0.12)	(-0.81)	(0.30)	(0.29)
	# funds	59	134	45	
high	Ex. Ret.	9.62**	10.84***	11.52***	1.90**
		(2.42)	(2.76)	(2.86)	(2.51)
	Alpha	-0.95	-0.03	0.36	1.31*
		(-1.18)	(-0.04)	(0.44)	(1.91)
	# funds	37	149	51	

Mutual funds are sorted into three groups (20-60-20) based on loadings change activity, which is measured by average absolute loading changes across MKT, SMB, HML and MOM. Independently, mutual funds are also sorted into three groups (20-60-20) based on tactical investment skill, which is estimated by rolling 5-year regressions of quarterly excess return on prior quarter loading change activity. For each of the total nine groups in each month, mutual funds' monthly before-fee excess returns over risk-free rate are averaged. Then for each group, the time series of monthly excess return is used to calculate the average excess return and to run a four-factor Carhart model to obtain an alpha. Both excess return and alpha are annualized and reported in percentage, with t-statistics in parentheses. Significance levels are at 10%, 5% and 1%

Appendix

A.I Data construction

We use the objective code to pick domestic diversified equity funds and use index fund flag, ET (Exchange Traded) flag and fund name to further filter out passive funds. Specifically, to select domestic diversified equity funds, we use data on the CRSP objective code to pick funds with codes starting with 'ED' (equity domestic) and to drop funds with codes starting with 'EDS' (equity domestic sector), 'EDYH' (equity domestic yield hedge), and 'EDYS' (equity domestic yield short). To further filter out passive funds, we use data on index fund flag and ET flag, which are available from June 2003, to exclude funds with any index fund flag or with ET flag being 'F.' For funds before June 2003, we rely on fund name to drop funds with names including 'Index' or 'Idx.' One problem is that some funds do not have names in some periods and some index funds may not manifest in their names. We may have accidentally included some index funds. However, index funds by construction should consistently have a high market exposure and very low factor loadings, and index funds should have very small changes in loadings.

A.II Results by each factor loading

Tables A1 through A4 present similar regressions as in Table 1.2, but the dependent variable is the absolute loadings change in each of the four factors rather than the average across all factors. Because we are not averaging the changes in these tables, the dependent variable tends to be more noisy. Overall the results are similar to the results in the main specification, but the significance levels are somewhat lower.

A.III Alternative specification: the effect of positive and negative returns and fund flows

The results in the main text show the relationship between flow or return rank and style changes. The reason we use rank instead of actual flow and return is to decrease noise. Large flows and returns can be quite extreme, even after winsorization. Using the rank reduces that variability to ensure that results are not driven by it.

However, it is useful to check whether or not the results shown in Table 1.2 are robust to using actual fund flows and returns instead. In the main tables, we used percentile ranks in order to mitigate the influence of outliers. Now, we use raw returns and fund flows winsorized at 1% and 99% in each quarter. Additionally, instead of a three-segment piecewise linear model, we estimate a two-piece, V-shaped, linear specification containing positive and negative linear segments for fund flows, alphas and lagged alphas.

Table A5 reports the results. As previously, the first specification (column 1) includes only fund flow—outflow and inflow—and controls only for the lagged absolute value of the loadings. Even though the noise is larger than in the main specification, we find large and highly statistically significant coefficients on both outflow and inflow. Controlling for returns and lagged returns as well as volatility (column 2) cuts the coefficient magnitude on both outflows (inflows) in less (more) than half and shows that there are large effects of returns on style changes. Including fund fixed effects (column 3) cuts the effect of return in less than half, though all the effects remain significant or close to significant. Including time fixed effects (column 4) cuts the effects of flows less than half and the effects of returns a little compared with column 2. Effects of outflows, negative and positive returns, lagged returns, are all statistically significant in the final, most restrictive, specification with both fund and time fixed effects. The effect of outflows and the effects of returns are significant at the 1% level.

We note that, when measuring style changes in response to actual flows and returns (instead of flow and return percentile rank) the effect of inflows is smaller as compared to outflows. The coefficient is smaller in four specifications, and about one quarter the size of the outflow effect in our preferred specification including fund and time fixed effects (column 5). Moreover, including time fixed effects (column 4 and column 5) cuts inflows' effects much more than it cuts outflows' effects. This could be that inflow has a downward sloping trend (Figure 1.6), and style changes also go down over time. (Figure 1.1). It could be that inflows' effects on style changes are partly driven by trends.

In Tables A6 through A9 we regress absolute value of the loadings changes in each of the four factors on the two-segment specification for past fund flows, alphas and lagged alphas and again obtain largely similar results to those when the explanatory variable is the average absolute change factor loading across the four factors.

Tables

Table A1: Regressions of the absolute change in MKT loading on three segments of percentiles of flows and returns

	(1)	(2)	(3)	(4)	(5)
Large outflow percentile	-5.34***	-2.95***	-2.38***	-1.87***	-1.58***
	(-8.14)	(-5.16)	(-4.45)	(-3.59)	(-3.26)
Intermediate flow percentile	-0.64**	-0.41*	-0.45*	0.65**	-0.06
	(-2.35)	(-1.68)	(-1.89)	(2.12)	(-0.23)
Large inflow percentile	5.37***	3.40***	3.02***	2.38***	1.56**
	(6.42)	(5.08)	(5.04)	(3.10)	(2.07)
Large neg. alpha percentile		-12.98***	-11.60***	-5.39***	-5.48***
		(-12.24)	(-11.05)	(-6.36)	(-6.40)
Intermediate alpha percentile		-0.62	-0.67*	-0.45	-0.48
		(-1.66)	(-1.89)	(-1.33)	(-1.49)
Large pos. alpha percentile		11.44***	9.57***	4.97***	4.57***
		(10.84)	(9.86)	(5.58)	(5.34)
Lagged large neg. alpha percentile		-10.22***	-8.75***	-2.86***	-2.82***
		(-9.59)	(-7.92)	(-3.33)	(-3.24)
Lagged intermediate alpha percentile		-0.32	-0.35	-0.14	-0.15
		(-1.09)	(-1.21)	(-0.56)	(-0.62)
Lagged large pos. alpha percentile		9.49***	7.66***	2.87***	2.59***
		(10.36)	(9.75)	(3.88)	(3.87)
Abs. loading	2.24*	-1.60	-5.09***	-0.96	-2.62
	(1.87)	(-1.41)	(-4.88)	(-0.46)	(-1.42)
Return std.		70.89***	142.99***	42.64***	88.58***
		(4.41)	(8.41)	(3.28)	(5.15)
Intercept	6.58***	11.25***	10.81***	8.46***	8.21***
	(6.01)	(10.44)	(12.34)	(4.16)	(4.95)
Obs.	155,624	155,624	155,624	155,624	155,624
R2	0.01	0.08	0.20	0.20	0.29
Fund fixed effect	NO	NO	NO	YES	YES
Time fixed effect	NO	NO	YES	NO	YES

$Large\ outflow\ percentile$ is $min(Flow\ percentile, 0.25)$, $Intermediate\ flow\ percentile$ is $min(Flow\ percentile - Large\ outflow\ percentile, 0.5)$, $Large\ inflow\ percentile$ is $(Flow\ percentile - Large\ outflow\ percentile - Intermediate\ flow\ percentile)$. Similarly, each quarter, percentiles of alpha and lagged alpha are split into three segments connected at 0.25, 0, and 0.75. Return std. is the standard deviation of monthly fund returns in the past 12 months. The absolute change in MKT loading between quarters is calculated as the dependent variable. The absolute value of MKT loading is used as Abs. loading. The dependent variable is in quarter t+1, and flow and alpha are in quarter t except lagged alpha in quarter t-1. The sample includes 3,874 funds from 1999Q2 to 2021Q4. T-statistics are clustered in two dimensions: fund and time. Significance levels are at 10%, 5% and 1%.

Table A2: Regressions of the absolute change in SMB loading on three segments of percentiles of flows and returns

	(1)	(2)	(3)	(4)	(5)
Large outflow percentile	-4.37***	-1.79***	-1.39**	-0.79	-0.45
	(-6.15)	(-3.22)	(-2.64)	(-1.31)	(-0.83)
Intermediate flow percentile	-1.31***	-0.82***	-0.76**	0.63	-0.22
	(-4.22)	(-2.82)	(-2.74)	(1.34)	(-0.65)
Large inflow percentile	5.47***	3.89***	3.92***	2.87***	1.58**
	(7.01)	(5.91)	(6.18)	(4.07)	(2.59)
Large neg. alpha percentile		-13.06***	-11.64***	-4.94***	-4.95***
		(-11.01)	(-9.53)	(-4.17)	(-4.10)
Intermediate alpha percentile		-0.10	0.00	0.04	0.01
		(-0.23)	(0.00)	(0.11)	(0.03)
Large pos. alpha percentile		12.34***	10.77***	4.96***	4.75***
		(11.75)	(10.71)	(5.50)	(5.36)
Lagged large neg. alpha percentile		-11.03***	-9.62***	-3.21***	-3.07***
		(-9.67)	(-8.49)	(-3.43)	(-3.24)
Lagged intermediate alpha percentile		0.31	0.37	0.47	0.42
		(0.80)	(0.98)	(1.39)	(1.27)
Lagged large pos. alpha percentile		10.72***	9.04***	3.18***	3.03***
		(8.40)	(8.85)	(2.89)	(2.95)
Abs. loading	-5.48***	-2.99***	-4.02***	1.27	-0.75
	(-5.30)	(-2.92)	(-5.16)	(0.70)	(-0.55)
Return std.		95.33***	139.80***	65.63***	109.69***
		(5.10)	(7.71)	(4.65)	(5.35)
Intercept	13.10***	11.84***	9.63***	7.84***	6.88***
	(31.71)	(10.93)	(8.40)	(6.73)	(5.08)
Obs.	155,624	155,624	155,624	155,624	155,624
R2	0.01	0.09	0.19	0.19	0.27
Fund fixed effect	NO	NO	NO	YES	YES
Time fixed effect	NO	NO	YES	NO	YES

$Large\ outflow\ percentile$ is $min(Flow\ percentile, 0.25)$, $Intermediate\ flow\ percentile$ is $min(Flow\ percentile - Large\ outflow\ percentile, 0.5)$, $Large\ inflow\ percentile$ is $(Flow\ percentile - Large\ outflow\ percentile - Intermediate\ flow\ percentile)$. Similarly, each quarter, percentiles of alpha and lagged alpha are split into three segments connected at 0.25, 0, and 0.75. Return std. is the standard deviation of monthly fund returns in the past 12 months. The SMB loading is adjusted by subtracting from it the loading of the SMB neutral portfolio. The SMB neutral portfolio invests half on the smaller stocks and the other half on the larger stocks. Based on the adjusted SMB loading, the absolute change in SMB loading between quarters is calculated as the dependent variable, and the absolute value of SMB loading is used as Abs. loading. The dependent variable is in quarter t+1, and flow and alpha are in quarter t except lagged alpha in quarter t-1. The sample includes 3,874 funds from 1999Q2 to 2021Q4. T-statistics are clustered in two dimensions: fund and time. Significance levels are at 10%, 5% and 1%.

Table A3: Regressions of the absolute change in HML loading on three segments of percentiles of flows and returns

	(1)	(2)	(3)	(4)	(5)
Large outflow percentile	-7.06***	-3.81***	-3.10***	-1.85**	-1.51**
	(-6.65)	(-4.03)	(-3.76)	(-2.36)	(-2.16)
Intermediate flow percentile	-0.99**	-0.56	-0.36	1.92***	0.02
	(-2.36)	(-1.37)	(-0.91)	(4.02)	(0.04)
Large inflow percentile	6.48***	4.00***	4.26***	5.16***	1.58**
	(5.80)	(4.27)	(5.20)	(4.87)	(2.05)
Large neg. alpha percentile		-20.43***	-17.73***	-7.61***	-8.19***
		(-9.50)	(-9.49)	(-4.58)	(-4.95)
Intermediate alpha percentile		0.44	0.65	0.78	0.54
		(0.75)	(1.18)	(1.34)	(0.97)
Large pos. alpha percentile		16.08***	13.04***	5.19***	5.11***
		(8.75)	(8.09)	(3.44)	(3.42)
Lagged large neg. alpha percentile		-16.17***	-13.54***	-3.93**	-4.19**
		(-8.47)	(-8.18)	(-2.46)	(-2.75)
Lagged intermediate alpha percentile		0.20	0.34	0.55	0.25
		(0.32)	(0.57)	(0.95)	(0.45)
Lagged large pos. alpha percentile		15.86***	12.59***	4.59***	4.71***
		(10.03)	(8.92)	(3.48)	(3.69)
Abs. loading	1.39	0.21	0.71	-1.42	1.56
	(0.83)	(0.14)	(0.58)	(-0.54)	(0.66)
Return std.		55.65**	154.91***	7.67	118.50***
		(2.12)	(7.31)	(0.32)	(5.37)
Intercept	15.21***	19.75***	13.78***	16.97***	10.81***
	(11.23)	(8.89)	(8.87)	(7.00)	(5.01)
Obs.	155,624	155,624	155,624	155,624	155,624
R2	0.00	0.04	0.20	0.14	0.27
Fund fixed effect	NO	NO	NO	YES	YES
Time fixed effect	NO	NO	YES	NO	YES

Large outflow percentile is $min(Flow\ percentile, 0.25)$, *Intermediate flow percentile* is $min(Flow\ percentile - Large\ outflow\ percentile, 0.5)$, *Large inflow percentile* is $(Flow\ percentile - Large\ outflow\ percentile - Intermediate\ flow\ percentile)$. Similarly, each quarter, percentiles of alpha and lagged alpha are split into three segments connected at 0.25, 0, and 0.75. Return std. is the standard deviation of monthly fund returns in the past 12 months. HML loading is adjusted by subtracting from it the loading of the HML neutral portfolio. The HML neutral portfolio invests half on the smaller stocks and the other half on the larger stocks. Based on the adjusted HML loading, the absolute change in HML loading between quarters is calculated as the dependent variable, and the absolute value of HML loading is used as Abs. loading. The dependent variable is in quarter t+1, and flow and alpha are in quarter t except lagged alpha in quarter t-1. The sample includes 3,874 funds from 1999Q2 to 2021Q4. T-statistics are clustered in two dimensions: fund and time. Significance levels are at 10%, 5% and 1%.

Table A4: Regressions of the absolute change in MOM loading on three segments of percentiles of flows and returns

	(1)	(2)	(3)	(4)	(5)
Large outflow percentile	-4.27***	-2.11***	-1.82**	-0.89	-0.56
	(-5.64)	(-3.03)	(-2.73)	(-1.35)	(-0.88)
Intermediate flow percentile	-1.50***	-1.04***	-1.00***	0.02	-0.83**
	(-4.91)	(-3.65)	(-3.45)	(0.06)	(-2.55)
Large inflow percentile	2.49***	1.32**	1.34**	0.49	-0.86
	(3.50)	(2.07)	(2.16)	(0.51)	(-1.35)
Large neg. alpha percentile		-15.56***	-14.49***	-8.92***	-8.95***
		(-9.76)	(-8.81)	(-5.75)	(-5.50)
Intermediate alpha percentile		0.05	0.13	0.16	0.07
		(0.09)	(0.22)	(0.26)	(0.12)
Large pos. alpha percentile		11.84***	10.69***	5.73***	5.55***
		(7.55)	(6.69)	(3.98)	(3.71)
Lagged large neg. alpha percentile		-9.49***	-8.51***	-3.04**	-3.08**
		(-7.20)	(-7.21)	(-2.59)	(-2.71)
Lagged intermediate alpha percentile		-0.40	-0.36	-0.24	-0.36
		(-0.78)	(-0.72)	(-0.46)	(-0.69)
Lagged large pos. alpha percentile		9.26***	7.96***	3.11***	2.89**
		(7.80)	(7.11)	(2.90)	(2.68)
Abs. loading	12.31***	9.01***	9.91***	6.61***	8.23***
	(6.34)	(4.41)	(5.90)	(2.93)	(4.43)
Return std.		49.84**	83.80***	32.88	78.81***
		(2.44)	(5.23)	(1.47)	(4.05)
Intercept	11.17***	14.01***	11.87***	12.17***	10.11***
	(24.03)	(13.78)	(12.94)	(12.75)	(9.81)
Obs.	155,624	155,624	155,624	155,624	155,624
R2	0.03	0.06	0.21	0.12	0.26
Fund fixed effect	NO	NO	NO	YES	YES
Time fixed effect	NO	NO	YES	NO	YES

$Large\ outflow\ percentile$ is $min(Flow\ percentile, 0.25)$, $Intermediate\ flow\ percentile$ is $min(Flow\ percentile - Large\ outflow\ percentile, 0.5)$, $Large\ inflow\ percentile$ is $(Flow\ percentile - Large\ outflow\ percentile - Intermediate\ flow\ percentile)$. Similarly, each quarter, percentiles of alpha and lagged alpha are split into three segments connected at 0.25, 0, and 0.75. Return std. is the standard deviation of monthly fund returns in the past 12 months. MOM loading is adjusted by subtracting from it the loading of the MOM neutral portfolio. The MOM neutral portfolio invests half on the smaller stocks and the other half on the larger stocks. Based on the adjusted MOM loading, the absolute change in MOM loading between quarters is calculated as the dependent variable, and the absolute value of MOM loading is used as Abs. loading. The dependent variable is in quarter t+1, and flow and alpha are in quarter t except lagged alpha in quarter t-1. The sample includes 3,874 funds from 1999Q2 to 2021Q4. T-statistics are clustered in two dimensions: fund and time. Significance levels are at 10%, 5% and 1%.

Table A5: Regressions of average of absolute changes in four loadings on two segments of flows and returns

	1	2	3	4	5
Outflow	-8.70***	-5.07***	-3.82***	-0.21	-2.04***
	(-6.04)	(-4.85)	(-5.32)	(-0.20)	(-3.51)
Inflow	6.88***	3.10***	1.79***	2.84***	0.64*
	(7.49)	(4.66)	(4.91)	(4.14)	(1.94)
Neg. alpha		-77.79***	-61.88***	-42.15***	-30.27***
		(-12.37)	(-14.44)	(-7.28)	(-7.92)
Pos. alpha		84.03***	60.76***	45.26***	25.38***
		(11.41)	(10.16)	(7.06)	(5.49)
Lagged neg. alpha		-49.04***	-43.81***	-14.40*	-13.19***
		(-5.83)	(-11.64)	(-1.80)	(-4.54)
Lagged pos. alpha		85.30***	54.07***	46.70***	19.36***
		(10.92)	(11.90)	(5.85)	(4.54)
Abs. loading	8.47***	2.60**	0.46	4.51**	5.14***
	(4.11)	(2.09)	(0.46)	(2.55)	(3.53)
Return std.		27.83*	114.47***	12.79	84.82***
		(1.93)	(11.65)	(0.98)	(7.91)
Intercept	5.84***	5.43***	3.60***	6.55***	3.59***
	(5.37)	(6.27)	(4.73)	(5.84)	(3.39)
Obs.	155,624	155,624	155,624	155,624	155,624
R2	0.02	0.16	0.31	0.30	0.42
Fund fixed effect	NO	NO	NO	YES	YES
Time fixed effect	NO	NO	YES	NO	YES

$Outflow$ is $min(Flow, 0)$, $Inflow$ is $max(Flow, 0)$. Similarly, alpha and lagged alpha are split into two segments connected at zero. Return std. is the standard deviation of monthly fund returns in the past 12 months. SMB/HML/MOM loadings are adjusted by subtracting from them the loadings of SMB/HML/MOM neutral portfolios. SMB/HML/MOM neutral portfolios invest half on the smaller/value/past winner stocks and the other half on the larger/growth/past loser stocks. Based on these adjusted loadings, the absolute changes in four loadings between quarters are averaged as the dependent variable. Abs. loading is the average of absolute values of loadings on MKT, SMB, HML and MOM adjusted in the above way. The dependent variable is in quarter t+1, and flow and alpha are in quarter t except lagged alpha in quarter t-1. The sample includes 3,874 funds from 1999Q2 to 2021Q4. T-statistics are clustered in two dimensions: fund and time. Significance levels are at 10%, 5% and 1%.

Table A6: Regressions of the absolute change in MKT loading on two segments of flows and returns

	1	2	3	4	5
Outflow	-7.84***	-4.60***	-3.72***	-1.38	-1.97**
	(-5.33)	(-3.82)	(-4.18)	(-1.07)	(-2.60)
Inflow	5.95***	2.71***	1.69***	2.46**	1.05*
	(5.20)	(3.19)	(3.30)	(2.71)	(1.98)
Neg. alpha		-71.52***	-60.83***	-42.52***	-33.71***
		(-10.84)	(-13.66)	(-6.93)	(-8.22)
Pos. alpha		76.96***	55.24***	45.58***	27.89***
		(9.83)	(7.95)	(5.74)	(4.23)
Lagged neg. alpha		-52.95***	-43.90***	-24.32***	-17.26***
		(-5.89)	(-8.13)	(-2.92)	(-3.89)
Lagged pos. alpha		64.87***	42.03***	34.07***	16.22***
		(8.23)	(8.43)	(4.23)	(3.44)
Abs. loading	2.22*	-1.14	-4.70***	-1.24	-2.81
	(1.89)	(-1.08)	(-4.63)	(-0.60)	(-1.54)
Return std.		33.19**	124.44***	23.29*	81.50***
		(2.24)	(7.40)	(1.84)	(4.74)
Intercept	5.01***	4.44***	4.45***	6.20***	5.63***
	(4.79)	(4.97)	(5.83)	(3.27)	(3.59)
Obs.	155,624	155,624	155,624	155,624	155,624
Entity	3,874	3,874	3,874	3,874	3,874
Period	91	91	91.00	91	91
R2	0.01	0.11	0.20	0.21	0.29
Fund fixed effect	NO	NO	NO	YES	YES
Time fixed effect	NO	NO	YES	NO	YES

$Outflow$ is $min(Flow, 0)$, $Inflow$ is $max(Flow, 0)$. Similarly, alpha and lagged alpha are split into two segments connected at zero. Return std. is the standard deviation of monthly fund returns in the past 12 months. The absolute change in MKT loading between quarters is calculated as the dependent variable. The absolute value of MKT loading is used as Abs. loading. The dependent variable is in quarter t+1, and flow and alpha are in quarter t except lagged alpha in quarter t-1. The sample includes 3,874 funds from 1999Q2 to 2021Q4. T-statistics are clustered in two dimensions: fund and time. Significance levels are at 10%, 5% and 1%.

Table A7: Regressions of the absolute change in SMB loading on two segments of flows and returns

	1	2	3	4	5
Outflow	-9.70***	-5.56***	-3.76***	-1.67	-1.78
	(-6.67)	(-5.34)	(-3.50)	(-1.43)	(-1.65)
Inflow	7.04***	3.14**	2.40***	3.26**	1.58**
	(4.49)	(2.73)	(3.53)	(2.65)	(2.36)
Neg. alpha		-65.34***	-54.42***	-34.30***	-25.72***
		(-5.72)	(-7.69)	(-3.32)	(-3.82)
Pos. alpha		89.75***	64.77***	53.97***	32.56***
		(9.02)	(8.39)	(5.36)	(4.06)
Lagged neg. alpha		-48.76***	-39.23***	-18.21**	-10.44**
		(-5.94)	(-6.83)	(-2.54)	(-2.06)
Lagged pos. alpha		84.50***	55.36***	49.86***	24.59**
		(7.17)	(5.69)	(4.33)	(2.46)
Abs. loading	-5.41***	-3.14***	-3.82***	0.94	-0.76
	(-5.22)	(-3.35)	(-4.83)	(0.55)	(-0.56)
Return std.		55.70***	123.04***	44.95***	100.95***
		(3.74)	(7.94)	(3.75)	(5.42)
Intercept	11.44***	5.75***	3.80***	5.99***	4.81***
	(30.12)	(7.04)	(4.50)	(6.44)	(4.24)
Obs.	155,624	155,624	155,624	155,624	155,624
Entity	3,874	3,874	3,874	3,874	3,874
Period	91	91	91.00	91	91
R2	0.02	0.11	0.19	0.20	0.27
Fund fixed effect	NO	NO	NO	YES	YES
Time fixed effect	NO	NO	YES	NO	YES

$Outflow$ is $min(Flow, 0)$, $Inflow$ is $max(Flow, 0)$. Similarly, alpha and lagged alpha are split into two segments connected at zero. Return std. is the standard deviation of monthly fund returns in the past 12 months. The SMB loading is adjusted by subtracting from it the loading of the SMB neutral portfolio. The SMB neutral portfolio invests half on the smaller stocks and the other half on the larger stocks. Based on the adjusted SMB loading, the absolute change in SMB loading between quarters is calculated as the dependent variable, and the absolute value of SMB loading is used as Abs. loading. The dependent variable is in quarter t+1, and flow and alpha are in quarter t except lagged alpha in quarter t-1. The sample includes 3,874 funds from 1999Q2 to 2021Q4. T-statistics are clustered in two dimensions: fund and time. Significance levels are at 10%, 5% and 1%.

Table A8: Regressions of the absolute change in HML loading on two segments of flows and returns

	1	2	3	4	5
Outflow	-9.42***	-5.58***	-3.90**	3.00*	-1.4
	(-4.92)	(-3.00)	(-2.75)	(1.97)	(-1.22)
Inflow	9.52***	4.61***	2.04***	4.83***	0.52
	(7.66)	(4.62)	(3.39)	(4.57)	(0.78)
Neg. alpha		-93.62***	-70.60***	-42.12***	-30.82***
		(-7.10)	(-6.92)	(-3.42)	(-3.22)
Pos. alpha		104.97***	64.75***	51.87***	21.84**
		(8.27)	(6.65)	(4.66)	(2.77)
Lagged neg. alpha		-61.82***	-50.98***	-11.21	-11.38*
		(-4.44)	(-7.48)	(-0.84)	(-1.90)
Lagged pos. alpha		127.61***	69.48***	74.94***	27.68***
		(8.50)	(8.80)	(4.87)	(3.73)
Abs. loading	1.39	-0.42	0.57	-1.52	1.58
	(0.83)	(-0.29)	(0.47)	(-0.59)	(0.68)
Return std.		5.57	139.82***	-15.62	112.13***
		(0.24)	(6.70)	(-0.71)	(5.14)
Intercept	13.02***	10.82***	5.53***	14.77***	7.67***
	(9.66)	(6.46)	(3.99)	(6.63)	(3.82)
Obs.	155,624	155,624	155,624	155,624	155,624
Entity	3,874	3,874	3,874	3,874	3,874
Period	91	91	91.00	91	91
R2	0.00	0.05	0.20	0.15	0.27
Fund fixed effect	NO	NO	NO	YES	YES
Time fixed effect	NO	NO	YES	NO	YES

$Outflow$ is $min(Flow, 0)$, $Inflow$ is $max(Flow, 0)$. Similarly, alpha and lagged alpha are split into two segments connected at zero. Return std. is the standard deviation of monthly fund returns in the past 12 months. HML loading is adjusted by subtracting from it the loading of the HML neutral portfolio. The HML neutral portfolio invests half on the smaller stocks and the other half on the larger stocks. Based on the adjusted HML loading, the absolute change in HML loading between quarters is calculated as the dependent variable, and the absolute value of HML loading is used as Abs. loading. The dependent variable is in quarter t+1, and flow and alpha are in quarter t except lagged alpha in quarter t-1. The sample includes 3,874 funds from 1999Q2 to 2021Q4. T-statistics are clustered in two dimensions: fund and time. Significance levels are at 10%, 5% and 1%.

Table A9: Regressions of the absolute change in MOM loading on two segments of flows and returns

	1	2	3	4	5
Outflow	-7.64***	-4.67**	-5.25***	-0.46	-3.36***
	(-3.90)	(-2.66)	(-4.17)	(-0.23)	(-3.05)
Inflow	2.64***	0.66	-0.29	0.23	-1.49**
	(3.29)	(0.83)	(-0.50)	(0.23)	(-2.41)
Neg. alpha		-77.16***	-54.27***	-52.70***	-32.83***
		(-8.01)	(-8.29)	(-5.17)	(-5.30)
Pos. alpha		58.14***	46.56***	30.80**	20.36*
		(4.45)	(3.99)	(2.53)	(1.90)
Lagged neg. alpha		-29.30**	-35.96***	-4.87	-14.22**
		(-2.69)	(-5.25)	(-0.44)	(-2.08)
Lagged pos. alpha		56.71***	33.50***	29.66**	8.46
		(5.25)	(5.63)	(2.72)	(1.51)
Abs. loading	12.21***	8.36***	10.12***	6.23**	8.35***
	(6.28)	(4.12)	(5.95)	(2.76)	(4.49)
Return std.		23.36	76.61***	17.96	75.16***
		(1.19)	(4.88)	(0.84)	(3.87)
Intercept	9.63***	7.45***	5.25***	9.22***	6.64***
	(20.12)	(9.73)	(7.39)	(10.65)	(7.74)
Obs.	155,624	155,624	155,624	155,624	155,624
Entity	3,874	3,874	3,874	3,874	3,874
Period	91	91	91.00	91	91
R2	0.03	0.06	0.21	0.12	0.26
Fund fixed effect	NO	NO	NO	YES	YES
Time fixed effect	NO	NO	YES	NO	YES

$Outflow$ is $min(Flow, 0)$, $Inflow$ is $max(Flow, 0)$. Similarly, alpha and lagged alpha are split into two segments connected at zero. Return std. is the standard deviation of monthly fund returns in the past 12 months. MOM loading is adjusted by subtracting from it the loading of the MOM neutral portfolio. The MOM neutral portfolio invests half on the smaller stocks and the other half on the larger stocks. Based on the adjusted MOM loading, the absolute change in MOM loading between quarters is calculated as the dependent variable, and the absolute value of MOM loading is used as Abs. loading. The dependent variable is in quarter t+1, and flow and alpha are in quarter t except lagged alpha in quarter t-1. The sample includes 3,874 funds from 1999Q2 to 2021Q4. T-statistics are clustered in two dimensions: fund and time. Significance levels are at 10%, 5% and 1%.

Table A10: Regressions of average of absolute changes in four loadings on three segments of percentiles of flows and returns, controlling lagged dependent variable

	1	2	3
Large outflow percentile	-2.86***	-1.67***	-1.48***
	(-7.30)	(-4.85)	(-4.47)
Intermediate flow percentile	-0.43**	-0.32*	-0.32*
	(-2.43)	(-1.92)	(-1.88)
Large inflow percentile	2.79***	1.92***	2.20***
	(6.93)	(5.78)	(6.83)
Large neg. alpha percentile		-9.81***	-9.89***
		(-9.79)	(-10.16)
Intermediate alpha percentile		0.02	0.1
		(0.08)	(0.39)
Large pos. alpha percentile		8.28***	7.96***
		(10.96)	(11.77)
Lagged large neg. alpha percentile		-5.81***	-5.90***
		(-6.67)	(-7.29)
Lagged intermediate alpha percentile		0.03	0.1
		(0.13)	(0.40)
Lagged large pos. alpha percentile		6.47***	6.16***
		(8.98)	(9.99)
Abs. loading	4.23***	2.19*	0.45
	(2.86)	(1.82)	(0.46)
Return std.		35.62***	86.92***
		(3.01)	(9.33)
Lagged abs. loading change	0.47***	0.41***	0.33***
	(20.89)	(16.52)	(19.30)
Intercept	4.12***	7.06***	6.67***
	-4.50	-6.85	-7.26
Obs.	155,624	155,624	155,624
R2	0.24	0.27	0.38
Fund fixed effect	NO	NO	NO
Time fixed effect	NO	NO	YES

$Large\ outflow\ percentile$ is $min(Flow\ percentile, 0.25)$, $Intermediate\ flow\ percentile$ is $min(Flow\ percentile - Large\ outflow\ percentile, 0.5)$, $Large\ inflow\ percentile$ is $(Flow\ percentile - Large\ outflow\ percentile - Intermediate\ flow\ percentile)$. Similarly, each quarter, percentiles of alpha and lagged alpha are split into three segments connected at 0.25, 0, and 0.75. Return std. is the standard deviation of monthly fund returns in the past 12 months. SMB/HML/MOM loadings are adjusted by subtracting from them the loadings of SMB/HML/MOM neutral portfolios. SMB/HML/MOM neutral portfolios invest half on the smaller/value/past winner stocks and the other half on the larger/growth/past loser stocks. Based on these adjusted loadings, the absolute changes in four loadings between quarters are averaged as the dependent variable. Abs. loading is the average of absolute values of loadings on MKT, SMB, HML and MOM adjusted in the above way. The dependent variable is in quarter t+1, and flow and alpha are in quarter t except lagged alpha in quarter t-1. The sample includes 3,874 funds from 1999Q3 to 2021Q4. T-statistics are clustered in two dimensions: fund and time. Significance levels are at 10%, 5% and 1%.

Table A11: Regressions of average of absolute changes in four loadings on three segments of percentiles of flows and returns, Quarter 1 and 2 each year

	(1)	(2)	(3)	(4)	(5)
Large outflow percentile	-5.63***	-2.80***	-2.11***	-1.37**	-0.99**
	(-6.91)	(-4.55)	(-3.88)	(-2.24)	(-1.99)
Intermediate flow percentile	-1.06***	-0.61**	-0.53*	0.71*	-0.21
	(-3.44)	(-2.25)	(-1.91)	(1.89)	(-0.72)
Large inflow percentile	5.91***	3.67***	3.50***	2.60***	1.33**
	(5.93)	(5.50)	(6.16)	(3.53)	(2.44)
Large neg. alpha percentile		-15.97***	-14.47***	-6.22***	-6.31***
		(-14.09)	(-13.14)	(-7.15)	(-6.86)
Intermediate alpha percentile		0.29	0.30	0.00	-0.02
		(0.71)	(0.80)	(-0.01)	(-0.05)
Large pos. alpha percentile		13.14***	11.27***	4.99***	4.64***
		(9.32)	(9.52)	(4.71)	(4.68)
Lagged large neg. alpha percentile		-13.07***	-11.44***	-4.27***	-4.10***
		(-9.72)	(-9.26)	(-3.88)	(-3.93)
Lagged intermediate alpha percentile		-0.06	-0.06	0.19	0.09
		(-0.16)	(-0.15)	(0.57)	(0.28)
Lagged large pos. alpha percentile		11.28***	9.17***	2.97***	2.49***
		(9.36)	(10.63)	(3.27)	(3.23)
Abs. loading	10.30***	5.02**	1.23	7.92***	6.71***
	(3.06)	(2.44)	(0.92)	(2.84)	(3.41)
Return std.		71.22**	136.88***	37.26	102.40***
		(2.75)	(9.69)	(1.59)	(7.43)
Intercept	6.06***	10.82***	9.36***	6.51***	4.57***
	(3.62)	(6.35)	(6.89)	(3.52)	(2.86)
Obs.	76,984	76,984	76,984	76,984	76,984
R2	0.03	0.14	0.32	0.32	0.46
Fund fixed effect	NO	NO	NO	YES	YES
Time fixed effect	NO	NO	YES	NO	YES

Large outflow percentile is $min(Flow\ percentile, 0.25)$, *Intermediate flow percentile* is $min(Flow\ percentile - Large\ outflow\ percentile, 0.5)$, *Large inflow percentile* is $(Flow\ percentile - Large\ outflow\ percentile - Intermediate\ flow\ percentile)$. Similarly, each quarter, percentiles of alpha and lagged alpha are split into three segments connected at 0.25, 0, and 0.75. Return std. is the standard deviation of monthly fund returns in the past 12 months. SMB/HML/MOM loadings are adjusted by subtracting from them the loadings of SMB/HML/MOM neutral portfolios. SMB/HML/MOM neutral portfolios invest half on the smaller/value/past winner stocks and the other half on the larger/growth/past loser stocks. Based on these adjusted loadings, the absolute changes in four loadings between quarters are averaged as the dependent variable. Abs. loading is the average of absolute values of loadings on MKT, SMB, HML and MOM adjusted in the above way. The dependent variable is in quarter t+1, and flow and alpha are in quarter t except lagged alpha in quarter t-1. The sample includes 3,874 funds from 1999Q3 to 2021Q4. T-statistics are clustered in two dimensions: fund and time. Significance levels are at 10%, 5% and 1%.

Table A12: Regressions of average of absolute changes in four loadings on three segments of percentiles of flows and returns, Quarter 3 and 4 each year

	(1)	(2)	(3)	(4)	(5)
Large outflow percentile	-5.89***	-3.06***	-2.46***	-1.41**	-1.14**
	(-7.83)	(-5.04)	(-4.44)	(-2.29)	(-2.03)
Intermediate flow percentile	-0.75**	-0.52**	-0.49**	0.92***	-0.24
	(-2.74)	(-2.27)	(-2.09)	(2.98)	(-1.05)
Large inflow percentile	5.59***	3.55***	3.46***	3.12***	0.93*
	(7.40)	(6.27)	(6.62)	(4.24)	(1.71)
Large neg. alpha percentile		-15.80***	-14.24***	-6.94***	-7.32***
		(-9.24)	(-9.03)	(-5.47)	(-5.54)
Intermediate alpha percentile		-0.27	-0.07	0.28	0.15
		(-0.67)	(-0.17)	(0.67)	(0.38)
Large pos. alpha percentile		13.52***	11.72***	5.55***	5.56***
		(13.80)	(13.02)	(6.24)	(6.37)
Lagged large neg. alpha percentile		-11.10***	-9.55***	-2.71**	-2.94***
		(-8.86)	(-8.39)	(-2.77)	(-2.98)
Lagged intermediate alpha percentile		0.05	0.23	0.1	0.04
		(0.12)	(0.62)	(0.28)	(0.12)
Lagged large pos. alpha percentile		12.34***	10.66***	4.01***	4.48***
		(10.93)	(12.10)	(4.30)	(5.26)
Abs. loading	6.81***	2.70	-0.60	3.92*	3.02
	(3.24)	(1.57)	(-0.42)	(1.83)	(1.53)
Return std.		59.36***	121.99***	23.98	80.62***
		(2.98)	(9.15)	(1.48)	(6.01)
Intercept	9.08***	13.33***	11.64***	10.05***	8.56***
	(8.14)	(10.38)	(10.79)	(8.29)	(6.10)
Obs.	78,640	78,640	78,640	78,640	78,640
R2	0.01	0.11	0.29	0.29	0.41
Fund fixed effect	NO	NO	NO	YES	YES
Time fixed effect	NO	NO	YES	NO	YES

$Large\ outflow\ percentile$ is $min(Flow\ percentile, 0.25)$, $Intermediate\ flow\ percentile$ is $min(Flow\ percentile - Large\ outflow\ percentile, 0.5)$, $Large\ inflow\ percentile$ is $(Flow\ percentile - Large\ outflow\ percentile - Intermediate\ flow\ percentile)$. Similarly, each quarter, percentiles of alpha and lagged alpha are split into three segments connected at 0.25, 0, and 0.75. Return std. is the standard deviation of monthly fund returns in the past 12 months. SMB/HML/MOM loadings are adjusted by subtracting from them the loadings of SMB/HML/MOM neutral portfolios. SMB/HML/MOM neutral portfolios invest half on the smaller/value/past winner stocks and the other half on the larger/growth/past loser stocks. Based on these adjusted loadings, the absolute changes in four loadings between quarters are averaged as the dependent variable. Abs. loading is the average of absolute values of loadings on MKT, SMB, HML and MOM adjusted in the above way. The dependent variable is in quarter t+1, and flow and alpha are in quarter t except lagged alpha in quarter t-1. The sample includes 3,874 funds from 1999Q3 to 2021Q4. T-statistics are clustered in two dimensions: fund and time. Significance levels are at 10%, 5% and 1%.

Table A13: After-fee returns of portfolios sorted on skill

Skill quintile	Average skill measure	Excess return	4-factor alpha
1 (low)	-0.65	8.23**	-1.91***
		(2.25)	(-3.72)
2	-0.25	8.70**	-1.34**
		(2.39)	(-2.17)
3	-0.04	8.94**	-1.18**
		(2.48)	(-2.48)
4	0.15	9.41**	-0.95*
		(2.54)	(-1.65)
5 (high)	0.49	9.78***	-0.83*
		(2.58)	(-1.67)
5 (high) - 1 (low)	1.14	1.55***	1.08**
		(2.69)	(2.07)

Every month, all actively managed equity mutual funds are sorted into quintiles based on their tactical investment skill, which is estimated as of the most recent quarter-end with rolling 5-year regressions of quarterly excess return on the average absolute change in factor loadings across MKT, SMB, HML and MOM factors. Monthly after-fee returns are then averaged across funds in each quintile, and the average annualized excess returns, their four-factor alphas are reported in the table in per cent, and the corresponding t-statistics are reported in parentheses. *, **, and *** indicate significance levels are at 10%, 5% and 1%, respectively.

Table A14: Before-fee returns of portfolios sorted on skill, alpha relative to the model of Cremers, Petajisto, and Zitzewitz (2010)

Skill quintile	Average skill measure	Excess return	Alpha
1 (low)	-0.65	9.33**	-0.40
		(2.54)	(-0.77)
2	-0.25	10.01***	0.28
		(2.73)	-0.44
3	-0.04	10.13***	0.31
		(2.78)	-0.68
4	0.15	10.64***	0.65
		(2.86)	(1.12)
5 (high)	0.49	10.91***	0.69
		(2.87)	(1.37)
5 (high) - 1 (low)	1.14	1.58***	1.09**
		(2.75)	(2.06)

Every month, all actively managed equity mutual funds are sorted into quintiles based on their tactical investment skill, which is estimated as of the most recent quarter-end with rolling 5-year regressions of quarterly excess return on the average absolute change in factor loadings across MKT, SMB, HML and MOM factors. Then for each group, the time series of before-fee monthly excess return is used to calculate the average excess return and to run a index-based model (Cremers, Petajisto, and Zitzewitz, 2010) to obtain an alpha. The index-based model includes the excess return on the S&P 500 index and the returns on the Russell 2000 index minus the return on the S&P 500 index, the Russell 3000 value index minus the return on the Russell 3000 growth index, and the Carhart's (1997) momentum factor. Both excess return and alpha are annualized and reported in percentage, with t-statistics in parentheses. *, **, and *** indicate significance levels are at 10%, 5% and 1%, respectively.

Table A15: Portfolios independently sorted on loading change activity and tactical investment skill, after-fee return

Loadings change		Skill: Low	Middle	High	High - Low
low	Ex. Ret.	8.56**	8.48**	9.22**	0.66
		(2.40)	(2.42)	(2.52)	(0.67)
	Alpha	-1.18	-1.32***	-0.89	0.28
		(-1.30)	(-2.62)	(-1.54)	(0.29)
	# funds	64	150	51	
high	Ex. Ret.	8.44**	9.44**	10.34**	1.90**
		(2.12)	(2.42)	(2.57)	(2.54)
	Alpha	-2.17***	-1.34**	-0.86	1.31**
		(-2.67)	(-1.99)	(-1.06)	(1.96)
	# funds	41	166	58	

Mutual funds are sorted into three groups (20-60-20) based on loadings change activity, which is measured by average absolute loading changes across MKT, SMB, HML and MOM. Independently, mutual funds are also sorted into three groups (20-60-20) based on tactical investment skill, which is estimated by rolling 5-year regressions of quarterly excess return on prior quarter loading change activity. For each of the total nine groups in each month, mutual funds' monthly excess returns over risk-free rate are averaged. Then for each group, the time series of monthly after-fee excess return is used to calculate the average excess return and to run a four-factor Carhart model to obtain an alpha. Both excess return and alpha are annualized and reported in percentage, with t-statistics in parentheses. Significance levels are at 10%, 5% and 1%

Table A16: Portfolios independently sorted on loading change activity and skill, before-fee alpha relative to the model of Cremers, Petajisto, and Zitzewitz (2010)

		Skill			
Loadings change		Low	Middle	High	High - Low
low	Ex. Ret.	9.66***	9.56***	10.34***	0.69
		(2.70)	(2.70)	(2.82)	(0.70)
	Alpha	0.19	-0.05	0.54	0.36
		(0.20)	(0.10)	(1.01)	(0.36)
	# funds	59	134	45	
high	Ex. Ret.	9.62**	10.84***	11.52***	1.90**
		(2.42)	(2.76)	(2.86)	(2.51)
	Alpha	-0.33	0.51	0.91	1.24*
		(0.40)	(0.71)	(1.05)	(1.76)
	# funds	37	149	51	

Mutual funds are sorted into three groups (20-60-20) based on loadings change activity, which is measured by average absolute loading changes across MKT, SMB, HML and MOM. Independently, mutual funds are also sorted into three groups (20-60-20) based on tactical investment skill, which is estimated by rolling 5-year regressions of quarterly excess return on prior quarter loading change activity. For each of the total nine groups in each month, mutual funds' monthly before-fee excess returns over risk-free rate are averaged. Then for each group, the time series of before-fee monthly excess return is used to calculate the average excess return and to run a index-based model (Cremers, Petajisto, and Zitzewitz, 2010) to obtain an alpha. The index-based model includes the excess return on the S&P 500 index and the returns on the Russell 2000 index minus the return on the S&P 500 index, the Russell 3000 value index minus the return on the Russell 3000 growth index, and the Carhart's (1997) momentum factor. Both excess return and alpha are annualized and reported in percentage, with t-statistics in parentheses. Significance levels are at 10%, 5% and 1%

Table A17: Portfolios conditionally sorted on loading change activity and skill (before-fee returns)

Panel A: 10-80-10

		Skill			
Loadings change		Low	Middle	High	High - Low
Low	Ex. Ret.	9.03**	9.45***	10.93***	1.89**
		(2.54)	(2.67)	(2.94)	(2.43)
	Alpha	-0.97*	-0.51	0.75	1.72**
		(-1.69)	(-0.99)	(1.04)	(2.30)
High	Ex. Ret.	9.00**	11.02***	13.13***	4.13***
		(2.25)	(2.77)	(3.13)	(3.65)
	Alpha	-1.53*	0.10	1.73	3.26***
		(-1.68)	(0.13)	(1.51)	(3.01)
	# funds	12	95	12	

Panel B: 20-60-20

		Skill			
Loadings change		Low	Middle	High	High - Low
Low	Ex. Ret.	9.77***	9.47***	10.4***	0.63
		(2.69)	(2.69)	(2.83)	(0.53)
	Alpha	0.08	-0.44	0.18	0.10
		(0.07)	(-0.96)	(0.35)	(0.08)
High	Ex. Ret.	9.64**	11.1***	11.55***	1.90**
		(2.42)	(2.83)	(2.87)	(2.55)
	Alpha	-0.98	0.24	0.42	1.40**
		(-1.26)	(0.35)	(0.51)	(2.04)
	# funds	48	142	47	

In Panel A, Mutual funds are first sorted into three groups (10-80-10) based on loading change activity, which is measured by average absolute loading changes across MKT, SMB, HML and MOM. Within each group, mutual funds are further sorted into three groups (10-80-10) based on skill, which is estimated by rolling 5-year regressions of quarterly excess return on prior quarter loading change activity. For each of the total nine groups in each month, mutual funds' monthly before-fee excess returns over risk-free rate are averaged. Then for each group, the time series of monthly before-fee excess return is used to calculate the average excess return and to run Carhart 4-factor model to obtain an alpha. Both excess return and alpha are annualized and reported in percentage, with t-statistics in parentheses. Panel B shows the 20-60-20 results of the above conditional double sorting process. Significance levels are at 10%, 5% and 1%

Table A18: Portfolios conditionally sorted on loading change activity and skill, before-fee alpha relative to the model of Cremers, Petajisto, and Zitzewitz (2010)

Panel A: 10-80-10

		Skill			
Loadings change		Low	Middle	High	High - Low
Low	Ex. Ret.	9.03**	9.45***	10.93***	1.89**
		(2.54)	(2.67)	(2.94)	(2.43)
	Alpha	-0.64	-0.20	1.16*	1.80**
		(-1.12)	(-0.39)	(1.65)	(2.41)
High	Ex. Ret.	9.00**	11.02***	13.13***	4.13***
		(2.25)	(2.77)	(3.13)	(3.65)
	Alpha	-0.86	0.65	2.15*	3.00***
		(-0.91)	(0.79)	(1.85)	(2.86)
	# funds	12	95	12	

Panel B: 20-60-20

		Skill			
Loadings change		Low	Middle	High	High - Low
Low	Ex. Ret.	9.77***	9.47***	10.4***	0.63
		(2.69)	(2.69)	(2.83)	(0.53)
	Alpha	0.39	-0.13	0.56	0.17
		(0.33)	(-0.28)	(1.10)	(0.14)
High	Ex. Ret.	9.64**	11.1***	11.55***	1.90**
		(2.42)	(2.83)	(2.87)	(2.55)
	Alpha	-0.35	0.77	0.95	1.31*
		(-0.45)	(1.09)	(1.11)	(1.88)
	# funds	48	142	47	

In Panel A, Mutual funds are first sorted into three groups (10-80-10) based on loading change activity, which is measured by average absolute loading changes across MKT, SMB, HML and MOM. Within each group, mutual funds are further sorted into three groups (10-80-10) based on skill, which is estimated by rolling 5-year regressions of quarterly excess return on prior quarter loading change activity. For each of the total nine groups in each month, mutual funds' monthly before-fee excess returns over risk-free rate are averaged. Then for each group, the time series of monthly before-fee excess return is used to calculate the average excess return and to run a index-based model (Cremers, Petajisto, and Zitzewitz, 2010) to obtain an alpha. The index-based model includes the excess return on the S&P 500 index and the returns on the Russell 2000 index minus the return on the S&P 500 index, the Russell 3000 value index minus the return on the Russell 3000 growth index, and the Carhart's (1997) momentum factor. Both excess return and alpha are annualized and reported in percentage, with t-statistics in parentheses. Panel B shows the 20-60-20 results of the above conditional double sorting process. Significance levels are at 10%, 5% and 1%

Chapter 2

Investors' sensitivity to index funds' fees

2.1 Introduction

One of the most well known patterns for mutual funds is a positive performance-flow relationship or "performance chasing", as shown in the literature (Gruber (1996), Chevalier and Ellison (1997), Berk and Green (2004)). These studies focused mainly or exclusively on active funds, and thus ignored index funds. One exception is Elton, Gruber, and Busse (2004), which focuses on S&P 500 index funds. This general omission was understandable and acceptable when index mutual funds (MFs) and index exchange-traded funds (ETFs) accounted for less than 5% of total assets in equity funds in 1995, but it becomes an issue today when the passive share of equity funds has risen to 48% in 2020 in the U.S. (Anadu, Kruttli, McCabe, and Osambela (2020)). As assets shift from active to passive funds, it is increasingly important to understand investor behavior regarding index funds.

Do investors of index funds also chase performance? If yes, the positive performance-flow relationship for index funds would essentially reflect a negative fee-flow relationship. Because different index funds tracking the same index should have the same before-fee return, cross-sectional variation in after-fee return should come only from cross-sectional variation in fees (if we control for tracking errors and transaction costs). In this sense, return is an alternative measure of fees, and a flow-performance relationship is essentially a flow-fee relationship.

Except Elton, Gruber, and Busse (2004), there is no literature focusing on the fee-flow relationships of index funds, although a related strand of literature documents that investors do not choose lowest fee index funds and then explains it from the perspective of search cost (Hortaçsu and Syverson (2004)), influence of brokers on unsophisticated investors (Boldin and Cici (2010)), and financial illiteracy (Choi, Laibson, and Madrian (2010)).

This study empirically examines fee-flow relationships of index funds. Different from the sample period from 1996 to 2001 in Elton, Gruber, and Busse (2004), this study examines the period from 2000 to 2016, during which there has been large fee decrease and increasing fee competition. Asset-weighted average monthly expense ratio of S&P 500 index funds in my sample drops from 0.019% in June 2000 to 0.008% in September 2016, as shown in Figure

2.1. Such a change in the index fund sector implies a stronger fee-flow relationship than before. And this study tests the fee-flow relation for different subsamples or in subperiods. Besides, this study examines not only S&P 500 index funds which are large cap funds but also Russell 2000 index funds which are mid-small cap funds.

The results show that one basis point difference in expense ratio between funds is negatively related with a monthly 0.12% flow difference for S&P 500 index funds. These effects are present when time effects are controlled for but disappear conditional on fund effects. There is little within variation in fund fees. The fee-flow relation is driven by fee differences across funds, rather than fee variation within funds over time. The fee-flow relation is slightly larger for the subgroups of larger funds or in the earlier part of the sample periods. 12b-1 fee is the component of expense ration that is used for marketing. 12b-1 fee captures marketing activities and thus could positively affect flows. Meantime, 12b-1 fees add an additional layer above management fees and could negatively affect flows as conditional cost. The results show the negative effect outweighs the positive one. It's consistent with the level of 12b-1 fee being decreasing.

Section 2.2 describes the data construction and summary statistics. Section 2.3 discusses prediction of future returns, fee-flow relations and the effects of 12b-1 fees. Section 2.4 concludes.

2.2 Data

2.2.1 Data construction

The data are from the Center for Research in Security Prices (CRSP) survivor-bias-free US mutual fund dataset. For each fund share class, the data includes fund share class code, fund share class name, fund objective code, index fund flag, ET (exchange-traded) flag, fund firm name, monthly total net assets (TNA), monthly after-fee return, expense ratio, and 12b-1 fee. Expense ratio and 12b-1 fee are available for some begin dates and end dates, and they are merged to each month between begin data and end date. For most funds, expense ratio and 12b-1 fee change every 12 months.

To select index funds, I first use the index fund flag to distinguish pure index funds from others. Pure index funds hold stocks in the index with the weights in the index. Second, the objective code “EDCL” which is available from June 1998 onward is used to distinguish S&P 500 index funds during the Jun 1998 - Sep 2016 period. For other index funds, fund names are used to perform a manual search and classify what index each fund tracks. Last, the ET flag can distinguish pure index ETFs from pure index MFs. This study starts with S&P 500 index funds which represent large-cap index funds and then analyzes Russell 2000 index funds which represent mid/small-cap index funds.

Following Chevalier and Ellison (1997), I drop observations in the months when mergers bring acquiring fund share classes unusually large flows. And observations with fund age less than two years or with fund size less than 10 million are dropped because of too much noise. Finally, observations which are shown to be pure index funds by the index fund indicator but are in fact enhanced index funds[1] by name search are removed. Finally, a total of 191 fund share classes of S&P 500 Index funds are in my sample. Among them, three are ETFs. The sample of Russell 2000 index funds includes 33 share classes, of which two are ETFs.

Following the literature (Chevalier and Ellison (1997), Sirri and Tufano (1998)), flow is calculated as the change in total net assets minus the total return earned $flow_t = (TNA_t - TNA_{t-1} * Ret_t)/TNA_{t-1}$, where TNA_t is a fund’s total net assets in month t, Ret_t is the fund’s total after-fee return including dividends in month t.

Fund fees in this study are measured by expense ratio. Expense ratio is the ratio of charged fees to investment amount. 12b-1 fee is one component of the expense ratio that is used for fund distribution and marketing. This research does not consider front load or rear load. Load usually has a few different levels depending on investment amount or

[1]Enhanced index funds invest on stocks within the index with different weights from the weights in the index or invest on derivatives of index to achieve a higher return than the index. In CRSP, an enhanced index fund has the index fund flag being "E".

holding period, both of which are related to investment strategy or constraints or investor preference. So, an analysis of load-flow relations would only be a group comparison of flows between different fund share classes designed for investors with different investment constraints, strategies, or preferences. It would be less likely an analysis of investors' fee-sensitivity.

To test whether fund fees are useful for predicting future returns of index funds, this research (following Elton, Gruber and Busse 2004) uses differential return and alpha to measure returns. Differential return is fund return minus index return. Alpha is estimated from regressions of excess after-fee fund return over one-month T-bill rate on excess index return over one-month T-bill rate. If funds perfectly track the index, beta would be one and thus differential return and alpha would be the same. But funds could hold cash or have other tracking errors, in which cases differential returns and alpha could be different.

Further, alpha is estimated from two-year rolling regressions of a fund's monthly excess returns on the index's monthly excess returns in the last two years, which could generate persistence in alpha and high predictive power of past alpha on future alpha. To avoid such high predictive power from construction, I also use daily return in each month to estimate alpha. Alpha generated in this way could have a high variation and a low predictive power for future alpha, because of the volatility of daily return. In this sense, the results from these two different estimates of alpha could provide one lower bound and one upper bound of past alpha's predictive power for future alpha.

The differences in risk across different index funds tracking the same index are from tracking errors. Beta measures a fund's systematic tracking error, and R square of regressions of alpha estimation measures random tracking error (Elton, Gruber, and Busse (2004)). Specifically, the more distant is Beta from one, the larger is the systematic tracking error. The lower is R square, the larger is the random tracking error. Like alpha, beta and R square are estimated using monthly return and two-year rolling regressions or estimated using dairy return in each month.

In the case of Russell 2000 Index funds, the index return is approximated by the return of iShares Russell 2000 Index fund, which has low expense and large size during most sample periods. This way of approximation is supported by the evidence from the case of S&P 500 Index funds. The after-fee return of Vanguard S&P 500 Index fund that has low expense and large size has a very small difference from the index return over the sample period.

2.2.2 Summary statistics

Summary statistics are reported in Table 2.1 and Table 2.2. On average, index funds perform below the index return by 0.05% each month, which is slightly larger than the average expense ratio of 0.04% each month. 12b-1 fees that are used for marketing are about half of expense ratio. Alpha estimated using daily return data and the alpha estimated from rolling monthly regressions are on average both similar to differential returns. But the alpha estimated using daily return data is much more volatile. Variations in tracking errors in both beta and R-square are small. Fund size has a large variation, which supports the usage of percentage flows. The average flow is negative and also very volatile. Smaller funds experience outflows and larger funds obtain inflows.

In the case of Russell 2000 index funds, flow and return are more volatile than those of S&P 500 index funds. The average expense ratio is one basis point higher than that of S&P 500 index funds. On average, the gap by which fund returns fall behind the index return is smaller than the expense ratio. It could be that fund managements are able to improve the performance.

2.3 Results

2.3.1 Prediction of future return of index funds using fund fees

Active funds are characterized by a positive relation between past returns and future fund flow. But fund returns are not persistent and past returns are not good predictors of future returns. In the case of index funds, the actual fee-flow relation

As shown in Table 2.3 and Table 2.4, for S&P 500 index funds, fund fees explain a higher portion (38%) of variation in future differential returns than past differential returns do (11%). For future alpha estimated by rolling regressions, fees explain 78%, while the past alpha by construction has a high explanatory power 98%, because alpha estimated from rolling regressions are highly persistent. For alpha estimated using daily return each month, fees explain 18%, while the past alpha by construction explains a low percent 6%, because alpha estimated using daily return has high volatility. With these two cases as bounds, fees' predictive power for future alpha is within a wide range of 18% - 78%.

In the case of Russell 2000 index funds, fees explain the variation in future differential return (34%) as much as past future differential return does. Compared with past alpha, fees explain less of the variation in future alpha no matter the alpha is estimated using daily return or from rolling regressions.

2.3.2 Relation between fees and flows of index funds

Table 2.5 and Table 2.6 show a negative relation between fees and flows of S&P 500 index funds. If a fund's expense ratio is one basis point lower than that of another fund, the lower-fee fund would have an additional flow of 0.12%. Past differential return has a positive effect on future flows. One basis point difference in past differential return is negatively related with a flow difference of 0.02%. The effect conditional on risk estimates using daily returns is slightly less statistically significant than that conditional on risk estimates using rolling monthly regressions. Probably because risk estimates using daily returns are more volatile than those from rolling monthly regressions. Past alpha estimated using daily data has no effect on future flows, while alpha estimated from rolling regressions has a positive effect. And the effect is equal to differential return's effect.

For Russell 2000 index funds, fees' effects are smaller than those of S&P 500 funds. One basis point difference in fees is negatively related with a flow difference of about 0.08% regardless of the method of alpha estimation. The effects are also weaker and only statistically at the 10% significance level. Past differential return or alpha has no effect on future flows.

The effects of fees on future flows are present and slightly larger when time effects are controlled for. But conditional on fund effects, the effects disappear. There is little within variation in fund fees. For S&P 500 index funds, fees' overall standard deviation is 0.032, the between standard deviation is 0.034, and the within deviation is 0.005. In the case of Russell 2000 index funds, the overall, between and within standard deviations are 0.036, 0.041 and 0.006 respectively. This is consistent with that for most funds in the sample, fees often change every year. For S&P 500 index funds, past returns' effects are also present and larger conditional on time effects. But when fund effects are considered, past alpha has a negative effect on future flows. During different periods of an average index fund's life, lower fees or higher returns are likely to appear in the more recent periods, during which the index fund achieves a large size (after rapid growth) and a relatively low percentage of flow.

Risk or tracking errors do not have statistically significant effects, possibly because variations of beta or R square are very small relative to the mean values. One exception is that for Russell 2000 index funds, the systematic tracking error estimated using daily return data has negative effects on future flows. But the effects become weaker and less statistically significant when time effects are controlled for. It could be during periods when there is more market wide volatility, funds are more likely to deviate from the index and there are more outflows.

As shown by the coefficients of ETF dummy, ETF funds have higher flows than other index funds. The effects disappear when fees are controlled for, which supports that ETFs' higher flows are driven by low fees. In the case of Russell 2000 index funds, ETF dummy has no effect on flows.

Fund age negatively affects flows, and the effect is robust regardless of estimation methods of alpha or time fixed effects. It could be that older funds phase in stable periods after rapid growth in the earlier periods. It could also be that funds become large after long existence and the percentage flow goes down. In the case of Russell 2000 funds, fund age has statistically significant effects only when time effects are controlled for.

It is possible that a fund's flow is related with other funds in the same fund family. If investors prefer popular or large fund companies, flows of one fund would be positively related with flows of other funds in the company. It's also possible that investors prefer fund companies that provide different types of funds to meet the overall need of asset allocation. For instance, Fidelity started offering the first zero-fee index fund in August 2018. After purchasing the zero-fee fund, investors may look at other funds in the same company. But the evidence in the sample is weak and the effects are not statistically significant for S&P 500 index funds. In the case of Russell 2000 index funds, flows are negatively affected by flows into other funds in the family when fund fixed effects are controlled for.

And the combined flow of all funds in each period also has no effect on individual fund flows. During periods when funds obtain inflows in aggregate, it is not that most funds experience inflows but rather flows across funds vary a lot. This is consistent with the large variation and the wide range of flows as in Table 2.1.

Table 2.8 reports the fee-flow relation of subsamples or in subperiods. For S&P 500 index funds, the results for subgroups of different fund sizes show that the fee-flow relation is slightly larger for larger funds. This is consistent with the fee-cutting competition among large index funds. The sub-periods results show that fee-flow relations hold in the earlier periods but not in the later periods. It could be driven by the rapid growth of index funds and the high concentration in the sector of index funds. As index funds grow to larger size in the later periods, flows in the percentage form become smaller. And these large funds often charge low fees. The largest five index funds in the sample on average account for 56% assets of all index funds, and they charge an average expense ratio of 0.007% relative to an average of 0.046% of other funds. These results are based on tracking errors estimated using daily returns. Results are similar when tracking errors are estimated from rolling regressions or when time effects are controlled for.

2.3.3 Relation between 12b-1 fee and flows of index funds

The above results are a mixture of different components of expense. 12b-1 fee is one component of expense ratio that is used for marketing or distribution. Since it represents marketing efforts, it could positively affect flows. On the other hand, it is an additional cost for investors and thus could negatively affect flows. To check the effect of this marketing component of fees on flows, I divide the whole sample into two groups: funds with 12b-1 fees vs. funds without 12b-1 fees.

As shown in Table 2.9, for funds without 12b-1 fee, past expense has a significant negative effect on flow. For funds with 12b-1 fee, 12b-1 fee also has a significant negative effect, which indicates that the negative effect of 12b-1 fee as additional cost outweighs the positive effect of 12b-1 fee as marketing efforts. Such negative effect of 12b-1 fees on index fund flows is different from the literature which finds 12b-1 fees have a positive effect on flows of active funds (Barber, Odean, and Zheng (2005), Bergstresser, Chalmers, and Tufano (2008)), but it is consistent with the fact that the 12b-1 fee level for funds that use it has been decreasing, as shown in Figure 2.2. These results are robust regardless of tracking error estimation or time effects.

2.4 Conclusion

This research documents a decline in asset-weighted average monthly fees across SP 500 index funds from 0.019% in 2000 to 0.008% in 2016, while the simple average level of monthly fees is always above 0.04% during the same period. It indicates that investors gradually concentrate more and more on low-fee funds during the sample period. Low-fee funds grow large and capture market shares. The largest five funds in the sample account for a large share of assets in each month, and the average level across months is 56%. The largest five funds also charge an average monthly expense ratio of 0.007% relative to an average of 0.046% of the remaining funds. These facts indicate a negative fee-flow relation, which is supported by further examination. The empirical results show one basis point difference in fees across funds is negatively related with a monthly flow difference of 0.12%. And the fee-flow relation is slightly larger for the subsample of larger funds or in the earlier subperiods. It could be the sector of index funds is close to the equilibrium where low-fee funds grow and capture market share. One component of fund expense ratio is 12b-1 fee, which is for marketing activities. Since it measures marketing activities, it could positively affect flows. On the other hand, as an additional cost, 12b-1 fee makes the overall fee higher and could discourage fee-sensitive investors and negatively affect flows. The overall effects appear to be negative, which is consistent with the fact 12b-1 fee is also decreasing in the sample period.

Figures

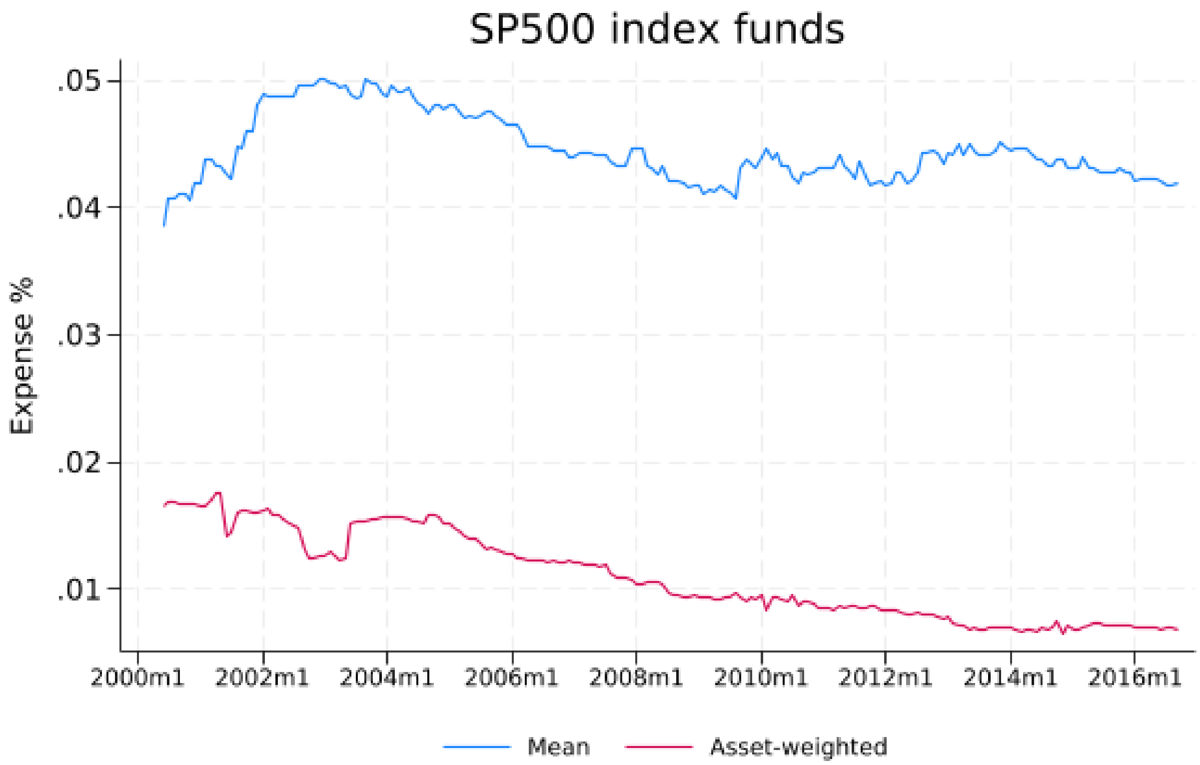

Figure 2.1: Monthly expense ratio of S&P 500 funds

This figure plots the simple average and asset-weighted average of S&P 500 index funds' expense ratio.

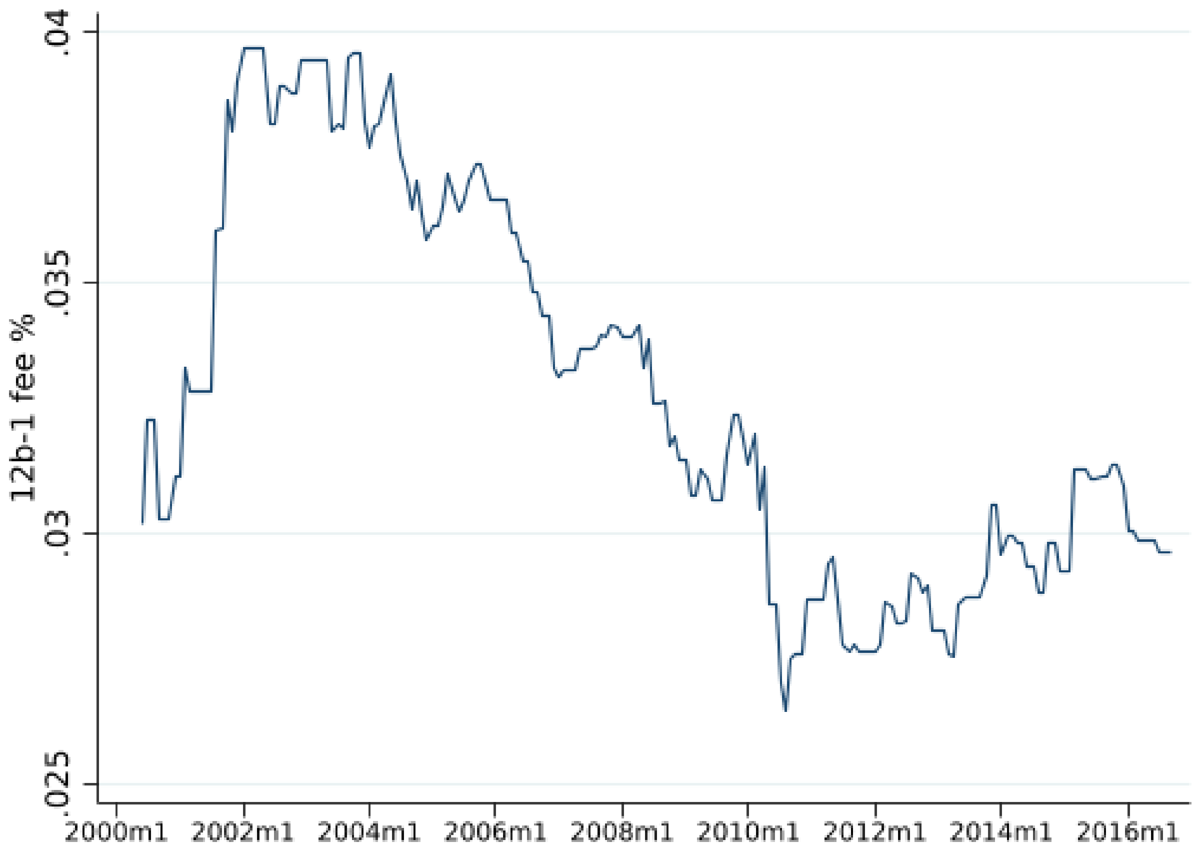

Figure 2.2: Monthly 12b-1 fee of S&P 500 index funds

This figure plots S&P 500 index funds' monthly 12-b1 fees.

Tables

Table 2.1: Summary statistics of S&P 500 index funds

	count	mean	sd	min	max
Flow	21,057	-0.40%	3.07%	-12.56%	14.63%
Expense ratio	21,057	0.04%	0.03%	0.00%	0.13%
12b-1 fee	14,789	0.02%	0.03%	0.00%	0.08%
Differential return	21,057	-0.05%	0.10%	-0.50%	0.24%
Alpha	21,057	-0.06%	0.22%	-1.09%	0.64%
Alpha (rolling)	21,057	-0.04%	0.07%	-0.17%	0.20%
Beta	21,057	1.001	0.011	0.965	1.033
R2	21,057	0.998	0.003	0.980	1.000
TNA (million)	21,057	2,677	9,140	11	58,281
Fund age (month)	21,057	144	61	47	379

This table reports summary statistics of fund flow, expense ratio, 12-b1 fees, differential return, alpha, beta, R2, total net assets (TNA) in millions, and fund age. Fund flow is defined as $flow_t = (TNA_t - TNA_{t-1} * Ret_t)/TNA_{t-1}$, where TNA_t and TNA_{t-1} are a fund's total net assets in month t and month t-1, respectively, and Ret_t is the fund's total after-fee return including dividends in month t. Expense ratio is the ratio of charged fees to investment amount. 12b-1 fee is one component of the expense ratio that is used for fund distribution and marketing. Differential return is fund return minus index return. Alpha is estimated from regressions of excess after-fee fund return over one-month T-bill rate on excess index return over one-month T-bill rate, using daily fund return in each month. From the same regression are Beta and R2 estimated. Alternatively, alpha is estimated using monthly fund return in a rolling two-year window. Fund age is the number of months since the fund inception date. The sample includes 191 fund share classes of S&P 500 index funds from 2000 to 2016.

Table 2.2: Summary statistics of Russell 2000 index funds

	count	mean	sd	min	max
Flow	2,365	0.02%	7.11%	-26.01%	37.62%
Expense ratio	2,365	0.05%	0.04%	0.01%	0.15%
12b-1 fee	1,385	0.02%	0.02%	0.00%	0.08%
Differential return	2,365	-0.03%	0.15%	-0.61%	0.79%
Alpha	2,365	-0.03%	0.15%	-1.18%	1.14%
Alpha (rolling)	2,365	0.00%	0.11%	-0.22%	0.39%
Beta	2,365	0.997	0.016	0.899	1.032
R2	2,365	0.998	0.004	0.936	1.000
TNA (million)	2,365	1,069	3,346	11	18,200
Fund age (month)	2,365	129	47	48	238

This table reports summary statistics of fund flow, expense ratio, 12-b1 fees, differential return, alpha, beta, R2, total net assets (TNA) in millions, and fund age. Fund flow is defined as $flow_t = (TNA_t - TNA_{t-1} * Ret_t)/TNA_{t-1}$, where TNA_t and TNA_{t-1} are a fund's total net assets in month t and month t-1, respectively, and Ret_t is the fund's total after-fee return including dividends in month t. Expense ratio is the ratio of charged fees to investment amount. 12b-1 fee is one component of the expense ratio that is used for fund distribution and marketing. Differential return is fund return minus index return. Alpha is estimated from regressions of excess after-fee fund return over one-month T-bill rate on excess index return over one-month T-bill rate, using daily fund return in each month. From the same regression are Beta and R2 estimated. Alternatively, alpha is estimated using monthly fund return in a rolling two-year window. Fund age is the number of months since the fund inception date. The sample includes 33 fund share classes of Russell 2000 index funds from 2000 to 2016.

Table 2.3: Prediction of future returns using fees and past returns: S&P 500 index funds

	Differential ret.	Differential ret.	Alpha	Alpha	Alpha	Alpha
Lagged differential ret.	0.265***					
	(15.136)					
Lagged expense		-0.966***		-0.831***		-0.966***
		(-66.165)		(-20.100)		(-155.183)
Lagged alpha			0.162***		0.985***	
			(10.992)		(177.912)	
Constant	-0.000***	-0.000	-0.001***	-0.000**	-0.000	0.000
	(-6.847)	(-1.845)	(-5.528)	(-2.843)	(-0.042)	(0.342)
R square	0.113	0.401	0.059	0.186	0.976	0.784
N	21,057	21,057	21,048	21,048	21,057	21,057
Alpha estimation			daily ret.	daily ret.	rolling	rolling

The table shows results of Fama MacBeth regressions. Differential return is fund return minus index return. Expense ratio is the ratio of charged fees to investment amount. Alpha is estimated from regressions of excess after-fee fund return over one-month T-bill rate on excess index return over one-month T-bill rate, using daily fund return in each month. Alternatively, alpha is estimated using monthly fund return in a rolling two-year window. ***, ** and * denote significance levels of 0.1%, 1% and 5% respectively.

Table 2.4: Prediction of future returns using fees and past returns: Russell 2000 index funds

	Differential ret.	Differential ret.	Alpha	Alpha	Alpha	Alpha
Lagged differential ret.	0.231***					
	(3.904)					
Lagged expense		-1.162***		-1.128***		-1.118***
		(-18.916)		(-15.142)		(-78.994)
Lagged alpha			0.216***		0.970***	
			(3.391)		(82.707)	
Constant	-0.000*	0.000***	-0.000***	0.000***	0.000	0.001***
	(-2.581)	(3.576)	(-5.257)	(3.869)	(1.748)	(6.701)
R square	0.341	0.346	0.319	0.283	0.962	0.722
N	2,365	2,365	2,365	2,365	2,365	2,365
Alpha estimation			daily ret.	daily ret.	rolling	rolling

The table shows results of Fama MacBeth regressions. Differential return is fund return minus index return. Expense ratio is the ratio of charged fees to investment amount. Alpha is estimated from regressions of excess after-fee fund return over one-month T-bill rate on excess index return over one-month T-bill rate, using daily fund return in each month. Alternatively, alpha is estimated using monthly fund return in a rolling two-year window. ***, ** and * denote significance levels of 0.1%, 1% and 5% respectively.

Table 2.5: Regressions of flow: S&P 500 index funds

	(1)	(2)	(3)	(4)	(5)	(6)
Expense	-11.600***			-11.614***		
	(-4.298)			(-4.313)		
Differential ret.		2.203			2.277*	
		(1.952)			(2.036)	
Alpha			0.129			2.231*
			(1.011)			(2.314)
Abs. of (beta-1)	-1.845	-4.553	-1.983	4.618	5.173	4.330
	(-0.508)	(-1.115)	(-0.549)	(1.034)	(1.132)	(0.931)
R2-1	11.652	0.739	5.796	16.181	18.948	19.519
	(0.596)	(0.036)	(0.300)	(1.216)	(1.416)	(1.364)
Age	-0.007***	-0.006***	-0.006***	-0.007***	-0.006***	-0.006***
	(-6.977)	(-6.214)	(-5.900)	(-6.844)	(-6.111)	(-6.143)
ETF dummy	0.254	0.568*	0.642*	0.268	0.576*	0.563*
	(0.888)	(2.002)	(2.164)	(0.942)	(2.058)	(2.058)
Aggregate flow	-0.008	-0.002	-0.006	-0.006	-0.001	-0.005
	(-0.371)	(-0.106)	(-0.276)	(-0.278)	(-0.027)	(-0.244)
Number of types in family	0.006	0.007	0.007	0.007	0.008	0.008
	(0.879)	(1.024)	(0.992)	(0.977)	(1.120)	(1.105)
Flow of others in family	-0.000	0.007	0.009	-0.001	0.006	0.009
	(-0.033)	(0.676)	(0.938)	(-0.093)	(0.588)	(0.906)
Constant	0.994***	0.442*	0.291	0.921***	0.385	0.386
	(3.626)	(2.132)	(1.414)	(3.382)	(1.846)	(1.816)
R square	0.026	0.017	0.012	0.026	0.018	0.014
N	21,057	21,057	21,057	21,057	21,057	21,057
Alpha estimation	daily ret.	daily ret.	daily ret.	rolling	rolling	rolling

Fund flow is defined as $flow_t = (TNA_t - TNA_{t-1} * Ret_t)/TNA_{t-1}$, where TNA_t and TNA_{t-1} are a fund's total net assets in month t and month t-1, respectively, and Ret_t is the fund's total after-fee return including dividends in month t. Expense ratio is the ratio of charged fees to investment amount. Differential return is fund return minus index return. Alpha is estimated from regressions of excess after-fee fund return over one-month T-bill rate on excess index return over one-month T-bill rate, using daily fund return in each month. From the same regression are Beta and R2 estimated. Alternatively, alpha is estimated using monthly fund return in a rolling two-year window. Fund age is the number of months since the fund inception date. ETF dummy equals one if a fund is Exchange Traded Fund. Aggregate flow of all funds each month, flows of other funds in the same fund family, and the number of fund types in the same fund family are also included. The t-statistics are two-dimensional clustered: by fund and by time. ***, ** and * denote significance levels of 0.1%, 1% and 5% respectively.

Table 2.6: Regressions of flow: Russell 2000 index funds

	(1)	(2)	(3)	(4)	(5)	(6)
Expense	-7.838			-7.413		
	(-1.842)			(-1.756)		
Differential ret.		0.283			0.004	
		(0.436)			(0.005)	
Alpha			0.669			1.196
			(0.618)			(0.879)
Abs. of (beta-1)	-15.228	-14.385	-15.520*	2.608	1.496	-2.849
	(-1.940)	(-1.778)	(-2.014)	(0.258)	(0.143)	(-0.264)
R2-1	-40.190	-38.466	-40.247	6.518	2.904	-4.265
	(-0.682)	(-0.652)	(-0.700)	(0.234)	(0.099)	(-0.146)
Age	-0.005	-0.005	-0.005	-0.005	-0.004	-0.005
	(-1.378)	(-1.268)	(-1.269)	(-1.331)	(-1.223)	(-1.256)
ETF dummy	0.078	0.286	0.269	0.191	0.385	0.342
	(0.125)	(0.458)	(0.428)	(0.309)	(0.620)	(0.569)
Aggregate flow	0.103	0.103	0.103	0.103	0.103	0.103
	(1.466)	(1.468)	(1.468)	(1.464)	(1.465)	(1.455)
Number of types in family	0.021	0.024	0.023	0.020	0.023	0.021
	(1.113)	(1.215)	(1.223)	(1.030)	(1.139)	(1.092)
Flow of others in family	-0.020	-0.017	-0.016	-0.021	-0.017	-0.015
	(-0.656)	(-0.533)	(-0.510)	(-0.647)	(-0.523)	(-0.477)
Constant	0.628	0.107	0.141	0.541	0.032	0.121
	(1.426)	(0.216)	(0.285)	(1.442)	(0.071)	(0.276)
R square	0.022	0.021	0.021	0.021	0.020	0.020
N	2,365	2,365	2,365	2,365	2,365	2,365
Alpha estimation	daily ret.	daily ret.	daily ret.	rolling	rolling	rolling

Fund flow is defined as $flow_t = (TNA_t - TNA_{t-1} * Ret_t)/TNA_{t-1}$, where TNA_t and TNA_{t-1} are a fund's total net assets in month t and month t-1, respectively, and Ret_t is the fund's total after-fee return including dividends in month t. Expense ratio is the ratio of charged fees to investment amount. Differential return is fund return minus index return. Alpha is estimated from regressions of excess after-fee fund return over one-month T-bill rate on excess index return over one-month T-bill rate, using daily fund return in each month. From the same regression are Beta and R2 estimated. Alternatively, alpha is estimated using monthly fund return in a rolling two-year window. Fund age is the number of months since the fund inception date. ETF dummy equals one if a fund is Exchange Traded Fund. Aggregate flow of all funds each month, flows of other funds in the same fund family, and the number of fund types in the same fund family are also included. The t-statistics are two-dimensional clustered: by fund and by time. ***, ** and * denote significance levels of 0.1%, 1% and 5% respectively.

Table 2.7: Regressions of flows with fixed effects: S&P 500 index funds

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Expense	-12.577***			11.169			-12.464***			11.351		
	(-4.986)			(0.998)			(-4.914)			(1.002)		
Differential ret.		3.377***			1.232			3.418***			1.236	
		(3.512)			(1.006)			(3.681)			(1.025)	
Alpha			0.229			-0.106			8.899***			-1.415*
			(1.443)			(-0.781)			(4.146)			(-2.238)
Abs. of (beta-1)	-3.596	-4.655	-4.102	1.012	-0.227	0.745	-11.204	-10.156	-25.284*	-2.459	-1.672	-2.498
	(-0.928)	(-1.215)	(-1.072)	(0.330)	(-0.065)	(0.244)	(-1.176)	(-1.114)	(-2.225)	(-0.639)	(-0.440)	(-0.609)
R2-1	25.257	6.194	13.146	-24.058	-29.502	-24.093	-10.291	-15.183	-19.702	-4.140	-0.516	-6.972
	(1.303)	(0.302)	(0.673)	(-1.365)	(-1.482)	(-1.334)	(-0.403)	(-0.576)	(-0.618)	(-0.356)	(-0.047)	(-0.588)
Age	-0.009***	-0.008***	-0.007***				-0.009***	-0.008***	-0.008***			
	(-7.441)	(-6.625)	(-6.174)				(-7.238)	(-6.513)	(-6.946)			
ETF dummy	0.188	0.521*	0.625**				0.238	0.547*	0.345			
	(0.885)	(2.295)	(2.622)				(1.091)	(2.406)	(1.628)			
Aggregate flow				0.010	0.013	0.010				0.008	0.011	0.009
				(0.561)	(0.826)	(0.562)				(0.452)	(0.690)	(0.465)
Number of types	0.004	0.006	0.005	-0.007	-0.012	-0.010	0.004	0.006	0.005	-0.007	-0.012	-0.010
in family	(0.568)	(0.803)	(0.737)	(-0.467)	(-0.792)	(-0.704)	(0.623)	(0.815)	(0.765)	(-0.488)	(-0.802)	(-0.678)
Flow of other	-0.002	0.006	0.009	-0.010	-0.011	-0.010	-0.002	0.006	0.001	-0.010	-0.011	-0.012
funds in family	(-0.220)	(0.620)	(0.927)	(-1.051)	(-1.100)	(-1.048)	(-0.173)	(0.637)	(0.140)	(-1.032)	(-1.107)	(-1.219)
Constant	1.253***	0.130	0.783**	-1.678**	-1.437*	-1.438*	1.938**	0.703	1.018	-1.580*	-1.306	-1.302
	(4.250)	(0.505)	(2.768)	(-2.616)	(-2.178)	(-2.164)	(2.620)	(1.079)	(1.353)	(-2.408)	(-1.953)	(-1.937)
R square	0.079	0.067	0.063	0.095	0.096	0.095	0.079	0.067	0.073	0.095	0.096	0.095
N	21,057	21,057	21,057	21,057	21,057	21,057	21,057	21,057	21,057	21,057	21,057	21,057
Effects	time	time	time	fund	fund	fund	time	time	time	fund	fund	fund
Alpha estimation	daily ret.	daily ret.	daily ret.	daily ret.	daily ret.	daily ret.	rolling	rolling	rolling	rolling	rolling	rolling

Fund flow is defined as $flow_t = (TNA_t - TNA_{t-1} * Ret_t)/TNA_{t-1}$, where TNA_t and TNA_{t-1} are a fund's total net assets in month t and month t-1, respectively, and Ret_t is the fund's total after-fee return including dividends in month t. Expense ratio is the ratio of charged fees to investment amount. Differential return is fund return minus index return. Alpha is estimated from regressions of excess after-fee fund return over one-month T-bill rate on excess index return over one-month T-bill rate, using daily fund return in each month. From the same regression are Beta and R2 estimated. Alternatively, alpha is estimated using monthly fund return in a rolling two-year window. Fund age is the number of months since the fund inception date. ETF dummy equals one if a fund is Exchange Traded Fund. Aggregate flow of all funds each month, flows of other funds in the same fund family, and the number of fund types in the same fund family are also included. The t-statistics are two-dimensional clustered: by fund and by time. ***, ** and * denote significance levels of 0.1%, 1% and 5% respectively. The specifications with time effects do not include combined flow as one explanatory variable, because the combined flow is common across funds in each period. The specifications with fund fixed effects have no fund age and ETF dummy. Because ETF dummy is fixed within fund. And fund age is fixed within fund.

Table 2.8: Subsample results: S&P 500 index funds

	Subgroups by fund asset size					Subperiods		
	smallest	quintile 2	quintile 3	quintile 4	largest	2000-2005	2006-2010	2011-2016
Expense	-10.277*	-13.864***	-7.634	-16.214**	-11.177**	-11.858***	-22.585***	-2.713
	(-2.185)	(-3.754)	(-1.308)	(-2.653)	(-2.722)	(-4.921)	(-6.886)	(-0.725)
Abs. of (beta-1)	-1.440	-0.321	-6.424	1.638	2.773	-0.111	8.136	-6.784
	(-0.158)	(-0.049)	(-0.916)	(0.219)	(0.451)	(-0.020)	(1.405)	(-1.107)
R2-1	9.475	38.959	2.737	-20.477	44.188	28.302	-8.578	53.706
	(0.274)	(1.431)	(0.083)	(-0.651)	(1.194)	(0.978)	(-0.301)	(1.801)
Age	-0.009**	-0.006***	-0.007***	-0.006***	-0.005***	-0.012***	-0.009***	-0.007***
	(-2.737)	(-3.541)	(-4.858)	(-3.866)	(-4.023)	(-5.243)	(-4.852)	(-5.253)
ETF dummy					0.194	0.466	0.075	0.222
					(0.555)	(1.853)	(0.304)	(0.475)
Aggregate flow	-0.005	-0.014	-0.029	-0.023	0.031	0.011	-0.036	0.020
	(-0.144)	(-0.530)	(-1.191)	(-1.127)	(1.235)	(0.648)	(-0.892)	(0.623)
Number of types	-0.007	0.010	-0.002	0.018	0.001	0.003	0.007	0.008
in family	(-0.298)	(0.716)	(-0.162)	(1.298)	(0.168)	(0.223)	(0.748)	(0.909)
Flow of other funds	-0.003	0.002	-0.014	0.007	-0.004	0.083**	-0.000	-0.005
in family	(-0.135)	(0.113)	(-0.471)	(0.586)	(-0.276)	(2.663)	(-0.009)	(-0.389)
Constant	1.270	1.188**	1.075*	0.627	0.969**	1.664***	1.286**	0.986*
	(1.829)	(2.659)	(2.508)	(1.548)	(3.015)	(4.299)	(3.236)	(2.485)
R square	0.021	0.031	0.023	0.026	0.024	0.032	0.064	0.018
N	4,284	4,215	4,211	4,216	4,131	6,137	7,456	7,464

Fund flow is defined as $flow_t = (TNA_t - TNA_{t-1} * Ret_t)/TNA_{t-1}$, where TNA_t and TNA_{t-1} are a fund's total net assets in month t and month t-1, respectively, and Ret_t is the fund's total after-fee return including dividends in month t. Expense ratio is the ratio of charged fees to investment amount. Beta and R2 are estimated from regressions of excess after-fee fund return over one-month T-bill rate on excess index return over one-month T-bill rate, using daily fund return in each month. Fund age is the number of months since the fund inception date. ETF dummy equals one if a fund is Exchange Traded Fund. Aggregate flow of all funds each month, flows of other funds in the same fund family, and the number of fund types in the same fund family are also included. The t-statistics are two-dimensional clustered: by fund and by time. ***, ** and * denote significance levels of 0.1%, 1% and 5% respectively.

Table 2.9: 12b-1 fees and flows

	S&P 500 index funds		Russell 2000 index funds	
Expense		-17.608**		-30.629***
		(-2.646)		(-3.356)
12b-1 fees	-17.628***		-28.371**	
	(-3.634)		(-3.217)	
other fees	-4.517		5.670	
	(-0.761)		(1.298)	
Abs. of (beta-1)	-2.333	-2.403	-13.262	-14.787
	(-0.463)	(-0.521)	(-0.694)	(-1.604)
R2-1	12.085	11.005	20.768*	-149.187
	(0.492)	(0.429)	(1.999)	(-1.363)
Age	-0.008***	-0.006***	-0.012*	-0.001
	(-5.217)	(-4.982)	(-2.128)	(-0.363)
ETF dummy	0.235	0.331	0.058	0.993
	(0.474)	(1.950)	(0.062)	(1.514)
Aggregate flow	-0.012	-0.005	0.055	0.129
	(-0.450)	(-0.243)	(1.032)	(1.288)
Number of types in family	0.008	0.003	0.034	-0.023
	(0.739)	(0.400)	(1.422)	(-1.168)
Flow of other funds in family	-0.018	0.013	-0.005	-0.031
	(-1.117)	(0.971)	(-0.204)	(-1.225)
Constant	1.215**	0.968**	1.521*	1.150***
	(2.659)	(2.712)	(2.367)	(6.573)
R square	0.038	0.018	0.021	0.046
N	9,890	11,042	997	1,347

Fund flow is defined as $flow_t = (TNA_t - TNA_{t-1} * Ret_t)/TNA_{t-1}$, where TNA_t and TNA_{t-1} are a fund's total net assets in month t and month t-1, respectively, and Ret_t is the fund's total after-fee return including dividends in month t. Expense ratio is the ratio of charged fees to investment amount. 12b-1 fee is one component of the expense ratio that is used for fund distribution and marketing. Beta and R2 are estimated from regressions of excess after-fee fund return over one-month T-bill rate on excess index return over one-month T-bill rate, using daily fund return in each month. Fund age is the number of months since the fund inception date. ETF dummy equals one if a fund is Exchange Traded Fund. Aggregate flow of all funds each month, flows of other funds in the same fund family, and the number of fund types in the same fund family are also included. The t-statistics are two-dimensional clustered: by fund and by time. ***, ** and * denote significance levels of 0.1%, 1% and 5% respectively.

Chapter 3

Two different exits: Prediction and performance of stocks that are about to stop trading.

Bibliography

Amihud, Yakov, and Ruslan Goyenko, 2013, Mutual fund's R^2 as predictor of performance, *Review of Financial Studies* 26, 667–694.

Anadu, Kenechukwu, Mathias Kruttli, Patrick McCabe, and Emilio Osambela, 2020, The shift from active to passive investing: Risks to financial stability?, *Financial Analysts Journal* 76, 23–39.

Angrist, Joshua D, and Jörn-Steffen Pischke, 2009, *Mostly harmless econometrics: An empiricist's companion* (Princeton university press).

Annaert, Jan, and Geert Van Campenhout, 2007, Time Variation in Mutual Fund Style Exposures, *Review of Finance* 11, 633–661.

Bai, Ting, Jens Hilscher, and Yitian Xiao, 2023, Two different exits: Prediction and performance of stocks that are about to stop trading, *Quarterly Journal of Finance* 13, 1–28.

Bams, Dennis, Roger Otten, and Ehsan Ramezanifar, 2017, Investment style misclassification and mutual fund performance, in *28th Australasian Finance and Banking Conference*.

Barber, Brad M, Xing Huang, and Terrance Odean, 2016, Which factors matter to investors? evidence from mutual fund flows, *Review of Financial Studies* 29, 2600–2642.

Barber, Brad M, Terrance Odean, and Lu Zheng, 2005, Out of sight, out of mind: The effects of expenses on mutual fund flows, *Journal of Business* 78, 2095–2120.

Barberis, Nicholas, and Andrei Shleifer, 2003, Style investing, *Journal of Financial Economics* 68, 161–199.

Bergstresser, Daniel, John MR Chalmers, and Peter Tufano, 2008, Assessing the costs and benefits of brokers in the mutual fund industry, *Review of Financial Studies* 22, 4129–4156.

Berk, Jonathan B., and Jules H. Van Binsbergen, 2015, Measuring skill in the mutual fund industry, *Journal of Financial Economics* 118, 1–20.

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

Berk, Jonathan B., and Jules H. Van Binsbergen, 2016, Assessing asset pricing models using revealed preference, *Journal of Financial Economics* 119, 1–23.

Boldin, Michael, and Gjergji Cici, 2010, The index fund rationality paradox, *Journal of Banking & Finance* 34, 33–43.

Bollen, Nicolas P. B., and Jeffrey A. Busse, 2001, On the timing ability of mutual fund managers, *Journal of Finance* 56, 1075–1094.

Brown, Keith C, W Van Harlow, and Laura T Starks, 1996, Of tournaments and temptations: An analysis of managerial incentives in the mutual fund industry, *Journal of Finance* 51, 85–110.

Brown, Keith C, W Van Harlow, and Hanjiang Zhang, 2009, Staying the course: The role of investment style consistency in the performance of mutual funds, *Available at SSRN 1364737*.

Busse, Jeffrey, Jing Ding, Lei Jiang, and Yuehua Tang, 2022, Artificial market timing in mutual funds, *Journal of Financial and Quantitative Analysis* pp. 1–56.

Busse, Jeffrey A, Jing Ding, Lei Jiang, and Ke Wu, 2023, Dynamic market timing in mutual funds, *Management Science*.

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

Chan, Louis KC, Hsiu-Lang Chen, and Josef Lakonishok, 2002, On mutual fund investment styles, *Review of Financial Studies* 15, 1407–1437.

Chang, Eric C, and Wilbur G Lewellen, 1984, Market timing and mutual fund investment performance, *Journal of Business* pp. 57–72.

Chevalier, Judith, and Glenn Ellison, 1997, Risk taking by mutual funds as a response to incentives, *Journal of Political Economy* 105, 1167–1200.

Chevalier, Judith, and Glenn Ellison, 1999, Career concerns of mutual fund managers, *Quarterly Journal of Economics* 114, 389–432.

Choi, James J, David Laibson, and Brigitte C Madrian, 2010, Why does the law of one price fail? an experiment on index mutual funds, *Review of Financial Studies* 23, 1405–1432.

Cohen, Randolph B, Christopher Polk, and Tuomo Vuolteenaho, 2003, The value spread, *Journal of Finance* 58, 609–641.

Cooper, Michael J, Huseyin Gulen, and P Raghavendra Rau, 2005, Changing names with style: Mutual fund name changes and their effects on fund flows, *Journal of Finance* 60, 2825–2858.

Cremers, KJ Martijn, Jon A Fulkerson, and Timothy B Riley, 2022, Active share and the predictability of the performance of separate accounts, *Financial Analysts Journal* 78, 39–57.

Cremers, KJ Martijn, and Antti Petajisto, 2009, How active is your fund manager? a new measure that predicts performance, *Review of Financial Studies* 22, 3329–3365.

Cremers, Martijn, Antti Petajisto, and Eric Zitzewitz, 2012, Should benchmark indices have alpha? revisiting performance evaluation, Discussion paper, National Bureau of Economic Research.

Daniel, Kent, and Tobias J Moskowitz, 2016, Momentum crashes, *Journal of Financial Economics* 122, 221–247.

Daniel, Kent D., Mark Grinblatt, Sheridan Titman, and Russ Wermers, 1997, Measuring mutual fund performance with characteristic-based benchmarks, *Journal of Finance* 52, 1035–1058.

DiBartolomeo, Dan, and Erik Witkowski, 1997, Mutual fund misclassification: Evidence based on style analysis, *Financial Analysts Journal* 53, 32–43.

Doidge, Craig, G Andrew Karolyi, and René M Stulz, 2017, The us listing gap, *Journal of Financial Economics* 123, 464–487.

Elton, Edwin J, Martin J Gruber, and Christopher R Blake, 2001, A first look at the accuracy of the crsp mutual fund database and a comparison of the crsp and morningstar mutual fund databases, *Journal of Finance* 56, 2415–2430.

Elton, Edwin J, Martin J Gruber, and Jeffrey A Busse, 2004, Are investors rational? choices among index funds, *Journal of Finance* 59, 261–288.

Elton, Edwin J, Martin J Gruber, and Christopher R Blake, 2012, An examination of mutual fund timing ability using monthly holdings data, *Review of Finance* 16, 619–645.

Fama, Eugene F., and Kenneth R. French, 1993, Common risk factors in the returns of stocks and bonds, *Journal of Financial Economics* 33, 3–56.

Frijns, Bart, Aaron Gilbert, and Remco C. J. Zwinkels, 2016, On the style-based feedback trading of mutual fund managers, *Journal of Financial and Quantitative Analysis* 51, 771–800.

Goetzmann, William N., Jonathan Ingersoll, and Zoran Ivković, 2000, Monthly measurement of daily timers, *Journal of Financial and Quantitative Analysis* 35, 257–290.

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

Haddad, Valentin, Serhiy Kozak, and Shrihari Santosh, 2020, Factor timing, *Review of Financial Studies* 33, 1980–2018.

Han, Xiao, Nikolai L. Roussanov, and Hongxun Ruan, 2022, Mutual fund risk shifting and risk anomalies, Working paper.

Henriksson, Roy D, 1984, Market timing and mutual fund performance: An empirical investigation, *Journal of Business* pp. 73–96.

Henriksson, Roy D., and Robert C. Merton, 1981, On market timing and investment performance. ii. statistical procedures for evaluating forecasting skills, *Journal of Business* 54, 513–533.

Hortaçsu, Ali, and Chad Syverson, 2004, Product differentiation, search costs, and competition in the mutual fund industry: A case study of s&p 500 index funds, *Quarterly Journal of Economics* 119, 403–456.

Huang, Jennifer, Clemens Sialm, and Hanjiang Zhang, 2011, Risk shifting and mutual fund performance, *Review of Financial Studies* 24, 2575–2616.

Ilmanen, Antti, Ronen Israel, Tobias J Moskowitz, Ashwin K Thapar, and Rachel Lee, 2021, How do factor premia vary over time? a century of evidence, *Journal of Investment Management* 19, 15–57.

Ippolito, Richard A, 1992, Consumer reaction to measures of poor quality: Evidence from the mutual fund industry, *The Journal of Law and Economics* 35, 45–70.

Jiang, George J, Tong Yao, and Tong Yu, 2007, Do mutual funds time the market? evidence from portfolio holdings, *Journal of Financial Economics* 86, 724–758.

Jiang, Hao, and Michela Verardo, 2018, Does herding behavior reveal skill? an analysis of mutual fund performance, *Journal of Finance* 73, 2229–2269.

Kacperczyk, Marcin, Stijn Van Nieuwerburgh, and Laura Veldkamp, 2014, Time-varying fund manager skill, *Journal of Finance* 69, 1455–1484.

Kacperczyk, Marcin, Clemens Sialm, and Lu Zheng, 2005, On the industry concentration of actively managed equity mutual funds, *Journal of Finance* 60, 1983–2011.

Lettau, Martin, Sydney C Ludvigson, and Paulo Manoel, 2018, Characteristics of mutual fund portfolios: Where are the value funds?, Discussion paper, National Bureau of Economic Research.

Levis, Mario, and Nicholas Tessaromatis, 2004, Style rotation strategies, *Journal of Portfolio Management* 30, 160–169.

Lynch, Anthony, and David K. Musto, 2003, How investors interpret past fund returns, *Journal of Finance* 58, 2033–2058.

Mamaysky, Harry, Matthew Spiegel, and Hong Zhang, 2008, Estimating the dynamics of mutual fund alphas and betas, *Review of Financial Studies* 21, 233–264.

Pastor, Lubos, Robert F Stambaugh, and Lucian A Taylor, 2015, Scale and skill in active management, *Journal of Financial Economics* 116, 23–45.

Pastor, Lubos, Robert F Stambaugh, and Lucian A Taylor, 2017, Do funds make more when they trade more?, *Journal of Finance* 72, 1483–1528.

Pettenuzzo, Davide, and Allan Timmermann, 2011, Predictability of stock returns and asset allocation under structural breaks, *Journal of Econometrics* 164, 60–78.

Polk, Christopher, Mo Haghbin, and Alessio De Longis, 2020, Time-series variation in factor premia: the influence of the business cycle, *Journal of Investment Management* 18, 69–89.

Polk, Christopher, Samuel Thompson, and Tuomo Vuolteenaho, 2006, Cross-sectional forecasts of the equity premium, *Journal of Financial Economics* 81, 101–141.

Sirri, Erik, and Peter Tufano, 1998, Costly search and mutual fund flows, *Journal of Finance* 53, 1589–1622.

Swinkels, Laurens, and Liam Tjong-A-Tjoe, 2007, Can mutual funds time investment styles?, *Journal of Asset Management* 8, 123–132.

Vidal-García, Javier, and Marta Vidal, 2022, Financial market anomalies, *Available at SSRN*.

Wermers, Russ, 2012, Matter of style: The causes and consequences of style drift in institutional portfolios, Working paper.