Positive Feedback Trading and Stock Prices: Evidence from Mutual Funds*

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Abstract

We show that mutual funds contribute to cross-sectional momentum and excess volatility through positive feedback trading. Stocks held by positive feedback funds exhibit much stronger momentum, almost doubling the returns from a simple momentum strategy. This "enhanced" momentum is robust to alternative measures of positive feedback trading and cannot be explained by other stock characteristics, ex-post firm fundamentals, fund flows, or herding. Moreover, enhanced momentum is almost fully reversed after one quarter, suggesting initial overshooting and subsequent reversal. We argue the most likely explanation is the price pressure from positive feedback trading. Finally, we relate positive feedback trading to mutual fund performance and show that it can positively predict a fund's return from active management.

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1 Introduction

Over the last three decades, the U.S. stock market experienced a fundamental shift in its ownership structure. Direct equity ownership from individuals has dropped to historical lows while a substantial fraction of the market is now held by mutual funds and other institutional investors (French 2008; Stein 2009; Stambaugh 2014). Given the massive trading volume coming from mutual funds and the amount of wealth they manage, it has become increasingly plausible that their trading behavior has a profound impact on return dynamics: they could very well represent the "marginal" investor in determining stock prices.

While this trend of "institutionalization" is undisputed, its implications for market efficiency and return predictability are far less clear. On the one hand, the traditional view suggests that institutional investors will act as arbitrageurs and correct for various forms of mispricing (Stambaugh 2014). As a result, higher institutional ownership will lead to a more efficient market and less predictable returns. On the other hand, opposing views emerge and argue that this may not be the case. These alternative views highlight institutional frictions such as leverage that can make the system prone to fire-sales and crashes (e.g., Shleifer and Vishny 1997; Kyle and Xiong 2001; Gromb and Vayanos 2002), as well as the lack of coordination among institutional investors (Stein 2009; Khandani and Lo 2011), which can exacerbate rather than correct for mispricing.

In this paper, we contribute to this ongoing debate through a particular lens: we analyze the effect of mutual funds' positive feedback trading on stock prices. We define positive feedback trading as the tendency to buy past winners and sell past losers, similar to earlier work such as De Long et al. (1990). Our exercise is deeply motivated by theoretical models such as Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), and Hong and Stein (1999). In these classic accounts, positive feedback traders exert price pressure as they buy past winners and sell losers, thereby generating initial momentum and subsequent reversal in the cross section of stocks. More recently, spurred by growing evidence on survey expectations (Greenwood and Shleifer 2014; Da, Huang, and Jin 2018), a number of papers argue that a model of extrapolators, whose behavior is in sync with positive feedback trading, can explain a wide range of empirical facts about asset prices (Barberis et al. 2015, 2018; Jin and Sui 2018).[1] The key innovation of our empirical analysis is the introduction of an institutional perspective: prior literature often characterizes positive feedback traders as naive individuals, but according to our exercise, even sophisticated investors such as mutual funds engage in positive feedback trading, and their trading could have a profound impact on stock prices in a way consistent with models of positive feedback trading.[2]

In particular, we address two fundamental questions that naturally arise in a framework of positive feedback traders. First, to the extent the positive feedback trading drives momentum, can we show *direct* empirical evidence? If this is indeed the case, a testable prediction follows that stocks traded by positive feedback funds should exhibit stronger momentum in the cross section, that is, these stocks should exhibit an "enhanced" momentum. Second, to the extent that this enhanced momentum results from the *temporary* price pressure from positive feedback trading, do we observe a full and immediate reversal? An initial overshooting, combined with a subsequent reversal, would then paint a coherent picture of how positive feedback trading leads to excess volatility in stock returns.

We begin our empirical analysis by first identifying positive feedback funds using the 13-F quarterly holdings database from 1980 to 2014. Specifically, in each quarter and for each fund, we run a *cross-sectional* regression by regressing the percentage change of each stock's position on that stock's past one-year return.[3] The resulting coefficient, measuring the sensitivity of holding changes to past one-year returns, is our main measure for positive feedback trading (PFT). This process produces a panel of *fund*-level PFT measures at the quarterly frequency. We examine the properties of this PFT measure and study the possible determinants. Importantly, we show that it is reasonably persistent over time, which means that a high-PFT fund now is more likely to stay as a high-PFT fund in the future.

Next, we aggregate the fund-level PFT measure at the stock level and study how these stock-level PFT measures could help predict future stock returns in the cross section. In each

[1]Early studies using survey expectations data include Frankel and Froot (1987, 1990) (exchange rate), Froot (1989) (Treasury bond), Case and Shiller (1988) (housing market), etc.

[2]A few papers show that some institutional investors behave as positive feedback traders: Lakonishok et al. (1992) shows evidence from pension managers; Grinblatt et al. (1995) classify mutual funds into momentum funds and contrarian funds to study their performances; and Wermers (1999) shows that positive feedback funds contribute to herding, which in turn affects stock prices.

[3]We adjust the percentage change of each stock's position for new purchases and fund flow induced trading as documented by Lou (2012).

quarter, we first independently sort all stocks into 25 portfolios based their past one-year returns and their most recent stock-level PFT measures. As an intermediate step, we show that mutual funds' trading is highly predictable: a winner (loser) stock experiences more buying (selling) if it is held more by high-PFT funds, because high-PFT funds consistently buy winners and sell losers.

Our first main result is that stocks held by high-PFT funds exhibit much higher momentum, which is consistent with the price pressure from positive feedback trading. In particular, a winners-minus-losers (WML) portfolio that long *high*-PFT winners and short *high*-PFT losers generate an annualized return of 10.3%, almost doubling the return (5.8%) from the unconditional portfolio. In contrast, a WML strategy conditional on *low*-PFT stocks only produces an annualized return of 3.0%, substantially lower than the unconditional benchmark. For brevity, we refer this phenomenon as "enhanced" momentum.

We perform several robustness checks on enhanced momentum. First, instead of sorting stocks into portfolios, we run a panel regression at the stock level. We find that, consistent with portfolio sorting, the interaction between stock-level PFT and past one-year return is positive and significant in predicting next quarter's return. Second, we construct three alternative measures for positive feedback trading, one of which is directly based on a fund's time-varying loading on the momentum factor, and enhanced momentum largely holds under these alternative measures. Third, we show that enhanced momentum holds in various subsamples: 1) in both the first (1980-1997) and the second (1998-2014) half of the sample, and 2) among stocks with low and high mutual fund ownership.

Additional subsample analysis reveals some interesting patterns. First, we find that enhanced momentum is stronger among *large* stocks, a result consistent with the evidence in Lou (2012) and Lou and Polk (2013), but different from the herding literature where price impact is more pronounced among small stocks (Lakonishok et al. 1992; Wermers 1999; Nofsinger and Sias 1999). Second, consistent with active trading driving price dynamics, enhanced momentum is strongest among active funds, less so among enhanced index funds, and virtually non-existent among pure index funds.

We conduct a few additional exercises to address alternative explanations for enhanced momentum. First, we rule out the possibility that this result is driven by some other stock characteristics by controlling for a long list of *pre*-formation stock characteristics across portfolios. We find that none of these stock characteristics can explain our result. Specifically, it cannot be explained by Fama-French three factors, other stock characteristics such as investment or idiosyncratic volatility, flow-induced trading (Lou 2012), or mutual fund ownership (Wermers 1999).

Second, we rule out a "selection" story, which articulates that high-PFT funds are better at "selecting" stocks with good *future* performance, either because they have superior stock-picking skills, or because they have some private information. First, to the extent that skills show up through better fund performance, we find no strong correlation between positive feedback trading and fund returns. Past fund returns are negatively associated with future positive feedback trading. Second, to the extent that positive feedback traders have some private information, the winners they buy should be ex-post "better," justified by exceptional fundamentals such as positive earnings surprises or positive abnormal returns during earnings announcement. We find that this is not the case: controlling post-formation earnings surprise and other fundamental news does not subsume enhanced momentum. We also rule out the possibility of a pure chance that we "happen" to select a set of high-momentum stocks by showing that there is substantial turnover for each of the 25 portfolios over time.

Third, we find that the enhanced momentum portfolio does not exhibit more fund inflows than the other portfolios. As a result, flow-induced trading (Lou 2012) is unlikely to drive our result. Finally, we discuss the similarities and differences between positive feedback trading and herding (e.g., Wermers 1999). While positive feedback trading can be thought of as a micro-foundation for herding, a number of deviations stand out in our empirical analysis: that enhanced momentum is stronger among large stocks, and, as we discuss below, that it is quickly reversed.

As our second main result, we show that enhanced momentum only occurs in the first quarter and is almost fully reversed in the second quarter. Although the *high*-PFT WML portfolio earns 1.82% *more* than the *low*-PFT one in the first quarter right after formation, it earns 1.40% *less* in the second quarter. In fact, post-formation cumulative returns over a two-year window are almost identical for the *high*-PFT and the *low*-PFT WML portfolios. Notably, this immediate reversion in returns further corroborates a price pressure mechanism and plausibly rejects an information-driven or fundamentals-driven mechanism. Under these alternative mechanisms, the difference in returns should stay permanent in the long run. Therefore, this return reversion further shows that mutual fund contributes to excess volatility in stock returns through positive feedback trading.

Finally, we explore the implications of our results for fund performance. On average, we find that high-PFT funds exhibit similar future performance to other funds regarding gross returns and factor-adjusted alphas. However, when we decompose fund returns into two parts, one based on active trading, defined by the return gap used in Kacperczyk, Sialm, and Zheng (2008), and the other one based on passive holdings, we find that high-PFT funds perform better in active trading. This outperformance in active trading, however, is counteracted by their underperformance on passive holdings.

Related literature. First, our analysis builds on and empirically tests the key idea in models of positive feedback trading: positive feedback trading creates temporary price pressure, triggering initial momentum and subsequent reversal in stock prices.[4] In our empirical strategy, we are agnostic about the underlying mechanism behind positive feedback trading: it can be rational (e.g., rational momentum trading or front-running as in De Long et al. 1990), bounded-rational (e.g., Hong and Stein 1999), psychological (e.g., representativeness in Barberis et al. 1998), or frictional (e.g., mutual fund benchmarking). Instead, we take positive feedback trading as given and study how it affects stock price dynamics. Specifically, we focus on one meaningful form of feedback trading based on stock returns of the past year, which is the look-back window of commonly used momentum strategy. Moreover, we want to highlight the institutional view we bring to the table: even sophisticated institutional investors engage in positive feedback trading, and their trading contributes to momentum as well as excess volatility. This result contributes to the ongoing debate on the implications

[4]In an early model, De Long et al. (1990) show that rational speculators have the incentive to front-run positive feedback traders, who further disrupt stock prices as they buy winners and sell losers. In several subsequent models, agents behave as positive feedback traders to generate cross-sectional momentum, but with different underlying mechanisms: for instance, self-attribution bias in Daniel, Hirshleifer, and Subrahmanyam (1998), representativeness in Barberis et al. (1998), and bounded-rationality in Hong and Stein (1999). More recently, spurred by growing evidence from survey expectations (Greenwood and Shleifer 2014), an ongoing discussion has been devoted to how extrapolators, who also behave as positive feedback traders, contribute to excess volatility and return predictability (e.g., **?**Jin and Sui 2018).

of institutionalization: even in the absence of individual investors, mutual funds can still disrupt stock prices through their positive feedback trading strategy.

Second, we contribute to the extensive literature that studies the relationship between momentum and mutual funds. Closest to our work is Lou (2012), which links momentum with flow-induced trading. The key difference between Lou (2012) and our paper is the source of price pressure: in Lou (2012), price pressure is ultimately driven by fund flows from retail investors, whereas mutual funds only act as the intermediary by passing these flows onto their stock holdings; in our paper, however, price pressure results from the active and conscious decisions made by mutual funds in the form of positive feedback trading. It is worth noting that we do not claim to *fully* explain momentum; indeed, even among low-PFT stocks, winners still outperform losers. Nonetheless, our results highlight that a potentially important source of momentum is mutual funds' positive feedback trading.

Third, our empirical results point out the "unanchored" nature of momentum, that is, the implementation of a momentum strategy lacks a fundamental anchor telling the trader when to stop (Stein 2009).[5] If a positive feedback trader knows about who the other positive feedback traders are and their current positions, there is an incentive for him to front-run other positive feedback traders to take advantage of their subsequent trading. This incentive is similar to the one described in De Long et al. (1990), where a rational speculator has the incentive to create an initial price increase to attract other positive feedback traders, except that, according to our results, this speculator now knows which stocks to target on: stocks held by other positive feedback traders. Moreover, it sheds light on the policy debate about holdings disclosure: more timely and accurate disclosure may lead other funds to take advantage of such information (Frank et al. 2004) and disrupt the market even more.

Finally, our paper is related to, but distinct from, the literature on mutual funds' herding behavior. On the one hand, Wermers (1999) shows that stocks heavily bought by mutual funds in a given quarter subsequently *outperform* stocks heavily sold by funds in that quarter and the gap in returns will not narrow until two quarters later. On the other hand, Dasgupta, Prat, and Verardo (2011) show that stocks persistently bought by mutual funds *underperform*

[5]In comparison, when a trader implements a value strategy, she knows it is time to stop when value stocks and growth stocks converge in their book-to-market ratios.

stocks persistently sold by mutual funds at long horizons. Our results differ from these prior studies in significant ways. In particular, previous papers focus on the information channel, that is, herding is driven by some common (private) information, whereas our paper focuses on the temporary price pressure channel. As a result, the superior returns from herding are long-lasting, but those in our paper quickly reverse. Also interestingly, the effect of herding on prices is more pronounced among small stocks, whereas our effect is much stronger among large stocks, indicating that different mechanisms are at play.

The rest of the paper is organized as follows. In Section 2, we elaborate on the dataset and how to measure positive feedback trading. We also discuss some basic properties about the measure. In Section 3, we examine the implications of positive feedback trading for stock returns. In Section 4, we discuss alternative mechanisms and the implications of our results on fund performance. We conclude in Section 5.

2 Measuring Positive Feedback Trading

2.1 Data

We construct our datasets by closely following Lou (2012). Quarterly mutual fund holdings data are from the Thomson-Reuters (formerly CDA/Spectrum) 13F database, and fund-level specific characteristics such as total net assets, net monthly returns, expense ratios are from the Center for Research in Security Prices (CRSP) survivorship-bias-free mutual fund database.[6] The two datasets are then merged using the MFLinks file provided by Wharton Research Data Services (WRDS).

In the data cleaning process, a few issues are worth noting. First, because we focus on the U.S. equity market, we only include domestic equities held by a U.S. fund. Second, we require the report date, the date on which holdings information is recorded, and the file date, the date on which a holdings report is filed, to be no more than six months apart. This ensures that holdings data are relatively recent. Third, similar in Lou (2012), because

[6]As in Lou (2012), monthly fund returns are calculated as net returns plus 1/12 of annual fees and expenses; the total net assets (TNA) is summed across all share classes; net returns and expense ratios are computed as the TNA-weighted average across all share classes; for other fund characteristics, the value from the share class with the largest total net assets are used.

some mutual funds misreport their investment objective codes, we require the ratio of the equity holdings to total net assets to be between 0.75 and 1.2, narrowing our focus primarily on equity funds. Fourth, to restrict our analysis on bigger funds, we require a minimum fund size of $1 million. Finally, we require that the total net assets (TNA) reported in CDA/Spectrum database and in the CRSP database do not differ by more than a factor of two.

In Panel A of Table 1, we report the number of funds, the median fund size, and the average fund size by years for our sample of mutual funds. As a comparison, in Panel B, we also report the same summary statistics for Lou (2012)'s sample. The two samples are very similar in all three dimensions. One difference is that we have slightly fewer funds in the earlier part of the sample, but more funds in the latter part of the sample. A second difference is that our sample covers eight additional years, from 2007 to 2014.

2.2 Main measure

As a first step of our analysis, we try to construct a time-varying positive feedback trading (PFT) measure for each mutual fund in our sample. Intuitively, a positive-feedback fund likes to buy securities after prices have risen and sell them after prices have fallen. There are, admittedly, several varieties of positive feedback trading, especially concerning the look-back horizon for calculating returns: trading strategies can be designed based on either short-term or long-term past returns, for instance. However, to link positive feedback trading with momentum, we focus on past one-year returns, which are typically used in a momentum strategy. Unlike in the typical implementation of a momentum strategy, we do not skip the most recent month, because we are averse to the presumption that these positive-feedback funds are following a momentum strategy. Instead, we want to capture positive feedback trading in a more general sense.

As our main measure, we estimate a fund's PFT by the sensitivity of changes in holdings to past one-year stock returns. Specifically, for fund i in quarter q, we run the following *cross-sectional* regression:

$$AdjHoldChange_{i,j,q} = a_{i,q} + b_{i,q} Ret_{j,q-5\rightarrow q-1} + \epsilon_{i,j,q}, \tag{1}$$

where $AdjHoldChange_{i,j,q}$ represents the stock j's *adjusted* holdings change in quarter q, and $Ret_{j,q-5\to q-1}$ represents stock j's past 1-year return from quarter $q-5$ to the preceding quarter, $q-1$. Notably, $AdjHoldChange_{i,j,q}$ and $Ret_{j,q-5\to q-1}$ are non-overlapping, which means that the coefficient $b_{i,q}$ reflects how fund i reacts to stocks' past one-year returns in making its portfolio decisions.

Specifically, $AdjHoldChange_{i,j,q}$ is defined by

$$AdjHoldChange_{i,j,q} \equiv \frac{Hold_{i,j,q} - Hold_{i,j,q-1} - FIT_{i,j,q}}{\left(Hold_{i,j,q} - Hold_{i,j,q-1}\right)/2}, \tag{2}$$

where $Hold_{i,j,q}$ denotes the number of shares of stock j held by fund i at the end of quarter q. The denominator is the average number of share of stock j between beginning and end of quarter q. We choose this specific form to account for the purchase of new stocks that are not in the fund's existing portfolio. The numerator measures the change in holdings, adjusted by $FIT_{i,j,q}$, that is, the change in holdings induced by fund flows in the current quarter. This takes into account the fact that fund holdings are not only driven by the managers themselves, but also passively dependent on the entry and exit of retail investors through fund flows. Specifically, when there is an outflow, $FIT_{i,j,q}$ is simply calculated by dividing the pro-rata outflow of stock j to its share price, as redemption is typically done dollar-to-dollar. However, when there is an inflow, there is a discount factor of 0.6, because, with inflows, funds tend to expand their holdings to other stocks.[7] By controlling for flow-induced trading, *AdjHoldChange* measures the *active* and *conscious* trading decisions made by mutual fund managers.

From Equation (1), we define fund i's positive feedback trading measure in quarter q as

$$PFT_{i,q} \equiv \hat{b}_{i,q} \tag{3}$$

From now on, we will use the italic PFT for the main PFT measure. Intuitively, it measures the sensitivity of trading decisions to past stock returns, whereby a larger PFT corresponds to a greater tendency of positive feedback trading.

[7]These adjustments are based on the results from Lou (2012); see the paper for more details.

2.3 Alternative measures

The specification of PFT reaps various benefits, but we also consider several alternative PFT measures that are related but different in meaningful ways.

Weight-based PFT measure. PFT uses the proportional change in holdings as the dependent variable. A different measure can be constructed by replacing the percentage change in holdings with the change in portfolio weight. Specifically, if we denote the quarter-q portfolio weight of stock j in fund i as $w_{i,j,q}$, then we can replace the left-hand side variable in Equation (1) as $w_{i,j,q} - w_{i,j,q-1}$ and construct a new measure for positive feedback trading. However, portfolio weights are known to drift over time as stock prices change, even when fund managers do not trade at all in the interim. Again, to capture the conscious decisions made by portfolio managers, we first calculate the passive weight of the stock *as if* the fund holds the same portfolio in the subsequent quarter. We then define portfolio weight change as

$$\Delta w_{i,j,q} \equiv w_{i,j,q} - w^*_{i,j,q}, \tag{4}$$

where $w^*_{i,j,q}$ is the passive weight of stock j at the end of quarter q after taking into account stock price changes from $q-1$ to q, and is given by

$$w^*_{i,j,q} = \frac{w_{i,j,q-1} Ret_{j,q-1\to q}}{\sum_{j\in i}\left(w_{i,j,q-1} Ret_{j,q-1\to q}\right)}. \tag{5}$$

We then replace adjusted share change with $\Delta w_{i,j,q}$ in Equation (1) and obtain our second measure, denoted by $PFT2$.

Grinblatt, Titman, and Wermers (1995) measure. Grinblatt, Titman, and Wermers (1995) propose a momentum investing measure of each fund based on the relationship between the weight and return of the stocks in fund's portfolio. We modify the "lag-0 momentum" (L0M; that is, there is no lag between past returns and trading) measure defined by the authors to make it time-varying and construct the measure at the quarterly frequency for fund i as

$$PFT3_{i,q} = \sum_{j \in i} (w_{i,j,q} - w_{i,j,q-1}) \, Ret_{j,q-5\to q-1} \tag{6}$$

where $w_{i,j,q}$ is fund i's portfolio weight of stock j at quarter q and $R_{j,q-5\to q-1}$ is the quarterly return of stock j from quarter $q-1$ to quarter $q-5$. The statistic is aimed at measuring the degree that the portfolio tilts towards to the past winner stocks. Specifically, for positive feedback traders, the change in weight $w_{j,q} - w_{j,q-1}$ and past return $Ret_{j,q-5\to q-1}$ tend to be of the same sign, resulting in a positive product. We enlist it as our third PFT measure, denoted by $PFT3$.

Factor-loading-based PFT measure. The returns of mutual funds that engage in positive feedback trading are likely to exhibit positive and sizable correlations with the momentum factor. One way to measure this time-varying correlation is to use the loadings on momentum factor in a series of rolling-window regressions. We achieve this by estimating the Fama-French-Carhart model each month with a 5-year rolling window

$$Ret_{i,m} = \alpha_{i,m} + PFT4_{i,m}MOM_m + \beta_{i,m}^{MKT}MKT_m + \beta_{i,m}^{SMB}SMB_m + \beta_{i,m}^{HML}HML_m + \epsilon_{i,m} \tag{7}$$

where $Ret_{i,t}$ is fund i's return in month t. For each quarter, we obtain the coefficient on MOM in the third month as our forth measure of PFT, denoted by $PFT4$. Note that, unlike PFT to $PFT3$, all of which measure a fund's behavior in a given quarter and are therefore non-overlapping, $PFT4$ summarizes a fund's behavior up to five years ago. This mechanically results in a strong autocorrelation for $PFT4$.

2.4 Summary statistics

Table 2 reports the summary statistics for four different measures of PFT. We have a total of 144,150 fund-quarter observations. Panel A focuses on distributional properties where all measures exhibit non-trivial dispersion. The median and mean of our main measure PFT are 0.13 and 0.28, respectively, suggesting that on average mutual funds tend to buy winners and sell losers. On the other hand, the other three measures have mean and median close to zero. Panel B tabulates the pairwise correlations across the four PFT measures. Though constructed using different methods, all the correlation coefficients are positive. In particular, PFT has sizable correlations with weight-based $PFT2$ and $PFT3$, with correlation coefficients of 0.57 and 0.45, respectively. Given the nature of rolling estimations, $PFT4$ is more persistent and has lower correlations with the other measures.

In Table 3, we further show the summary statistics of PFT measures by mutual funds investment objectives code (IOC), which are self-reported and collected by CRSP. We restrict the sample to funds that have valid IOC recordings from CRSP. Panel A reports the average, median, standard deviation, and number of observations for PFT while Panel B only shows the median for the other measures. Growth funds, particularly Aggressive Growth funds, exhibit a stronger tendency to engage in positive feedback trading: for all the four measures of PFT, their average is consistently the highest among all IOC groups. This is roughly consistently with their tendency to hold stocks with a low book-to-market ratio, often resulting from having a series of positive past returns. We also note that, even within a given IOC group, there is substantial variation across funds. This suggests that, despite the style a fund claims to be, the manager takes substantial discretion when managing the portfolio. After presenting these summary statistics, we winsorize all PFT measures at 1% and normalize them by their respective standard deviations for ease of exposition. Rest of the paper will use these normalized PFT measures. We will focus on PFT, but report results under alternative measures when necessary.

2.5 Persistence

Next, we investigate the persistence of PFT. As positive feedback trading may capture the inherent characteristics of a fund manager (for instance, extrapolative beliefs whereby the manager expects future returns to positively depend on past returns), we expect it to be reasonably persistent over time. At the same time, PFT may as well be time-varying since fund managers will design their strategies based on market conditions and they may switch from positive feedback trading to other strategies from time to time. Table 4 shows the panel regression results by regressing current PFT on past PFT, where we include time fixed effect to control for the time-variation in the aggregate market conditions and double-cluster standard errors by fund and quarter. Across all the specifications we consider, lagged PFTs always significantly predict future PFT at 1% level. The coefficients from univariate panel regressions (column 1 to 5) are always less than 1, indicating that a sizable portion of the variation is beyond the persistence.

Another way to gauge the within-fund persistence of PFT is to estimate the transition probability matrix for a mutual fund to move from one quintile to another in the subsequent period. Table 5 shows the transition matrices. Panel A uses quarterly observations, and Panel B uses annual observations, which are calculated as the average of four quarterly observations in a given year. The diagonal items in both matrices indicate what proportion of the funds stay in the same quintile from period to period. If PFT is randomly distributed from period to period, then we would expect the transition probability in each cell to be around 20%. This is clearly not the case: there are more funds staying in the same quintile, especially for quintile 1 and 5, where 33% and 31% of the funds remain in the same bin from quarter to quarter. The persistence for annual average PFT, shown in Panel B, is even stronger: around 40% of the quintile 1 and 5 funds do not move. Taking together, the evidence suggests that while positive feedback trading is time-varying, it is reasonably persistent at the fund level.

2.6 Determinants

To gain a deeper understanding about the sources of variation in PFT, we run panel regressions of PFT on a battery of fund-level explanatory variables at the quarterly frequency. Table 6 summarizes the results. We include IOC fixed effect to capture any unobserved heterogeneity across different investment objectives. Because PFT and many of the fund level characteristic variables are persistent over time, we cluster standard errors by fund and quarter.

The first variable we consider is the active fund dummy. A fund is regarded as active in our sample if it is not a pure index fund which passively tracks a specific index. By this definition, active funds have discretion over the portfolio choice and are more likely to have a higher PFT. We have found that active funds have, on average, 0.16 higher PFT. Similar results obtain when we narrow our scope to actively managed domestic equity funds.

The second variable we consider is the past year's return to the momentum strategy (MOM factor). We posit that when the momentum strategy performs well recently, the funds will more actively engage in the positive feedback trading possibly because as the signal becomes more salient the positive feedback mechanism becomes even stronger. The result from column (2) confirms this positive relationship between PFT and momentum strategy return with significance at 1% level.

The next two variables of interests are past year's fund gross return and fund flows. Specifically, past fund returns and fund flows negatively predict a fund's future PFT. To the extent that PFT can be interpreted as a more aggressive style of trading, this result suggests that funds that have performed well in the past with substantial fund inflows engage in less positive feedback trading. This evidence also suggests that, when past returns are high and fund flows are good, stock pickers, which are a large portion of the mutual fund sample, stick with their stock selection strategies rather than move to (momentum) factor bets.

Apart from these four variables, we include a number of fund characteristics such as fund size (TNA and TNA^2), prior factor returns to market, size, value factors, as well as some endogenous variable that are under the fund manager's control such as Active Share from Cremers and Petajisto (2009), turnover, expense ratio, management fees. Adding the additonal explanatory variables barely change the significance and magnitude of the previous considered determinants. Moreover, we find that fund size is positively and significantly related to the contemporaneous PFT and it has a significant non-linear effect on PFT. Funds with a higher turnover rate have a higher PFT. *Active Share,* which measures how the weights of a fund's holdings are different from those of benchmark index the fund tracks, is negatively related to PFT. This may come as a surprise to many since we claim that positive feedback trading PFT measures active portfolio decision beyond flow-induced buying and selling. This again indicates that funds with high PFT, by the definition of Cremers and Petajisto (2009) , are more likely to fall into the category of "factor bets" rather than active stock selection.[8]

[8]This behavior may be attributed to a theory of salience or inattention. As the stocks in the benchmarks are closely watched by the manager, these signals are more salient to her and she would pick these stocks when she starts following positive feedback trading.

3 Results for the cross section of stocks

Positive feedback traders, after observing past returns, tend to buy (sell) past winners (losers) and, in doing so, they push up (down) their prices even more with the price pressure associated with their trading. As a result, a natural application of positive feedback trading is to explain momentum. In this section, we first analyze whether positive feedback trading contributes to momentum.

We first aggregate the fund-level PFT to the stock level by computing the weighted average of PFT among mutual funds that own the stock. Specifically, in each quarter q, we calculate

$$SPFT_{j,q} = \sum_i \frac{Hold_{i,j,q}}{\sum_{j \in i} Hold_{i,j,q}} PFT_{i,q}, \tag{8}$$

where $Hold_{i,j,q}$ is the number of shares of stock j held by fund i at the end of quarter q. Therefore, $SPFT_{j,q}$ measures the average tendency of positive feedback trading for stock j's underlying investors. From now on, we refer to the variable $SPFT$ simply as stock-level PFT.

To study how $SPFT$ relates to cross-sectional momentum, in each quarter, we independently sort all stocks into 25 portfolios based their on past one-year returns and the most recent $SPFT$, and we then study value-weighted mutual fund ownership changes and returns in the subsequent quarter for each portfolio. Panel B of Table 7 reports the average number of stocks in each of the 25 portfolios. As can be seen, the numbers are reasonably high, ranging from 59 to 135. Moreover, there is not a single quarter when we have zero stock in any of the 25 portfolios. Therefore, any results in the following subsections are unlikely to be driven by a very small number of stocks in the portfolios.

3.1 Predictable trading behavior

As a first step, we show that mutual fund trading behavior with consistent with their PFT, and stock-level ownership changes are highly predictable based on their $SPFT$. The intuition is straightforward: high-PFT funds buy winners and sell losers in a more aggressive way, hence a winner (loser) stock experiences more buying (selling) if it is held by high-PFT

funds, i.e., if it has a high $SPFT$.

Panel A of Table 7 shows the value-weighted mutual fund ownership changes for the 25 portfolios. The results conform with our intuition: among high-$SPFT$ stocks, a winner on average experiences 5.3% more buying than losers; as a comparison, among low-$SPFT$ stocks, a winner on average only experiences 1.6% more buying. These differences are rather sizable and monotonically increase from low-$SPFT$ stocks to high-$SPFT$ stocks.

3.2 Predictable stock returns

Main results. Panel C of Table 7 shows the valued-weighted average quarterly return for each portfolio, annualized for ease of comparison. t-statistics are reported in the parentheses under each return number. The last row is the return to the winner-minus-loser (WML) strategy for each of the five *SPFT* levels. Noticeably, WML returns increase monotonically from low *SPFT* to high *SPFT* stocks, consistent with positive feedback trading contributing to cross-sectional momentum. The difference is substantial: a WML strategy delivers annualized returns of 3.0% ($t = 0.80$) and 10.3% ($t = 2.54$), respectively, in the lowest and highest *SPFT* quintiles. The top quantile, in particular, delivers an average return that almost doubles that (5.8%) from the unconditional WML strategy. For brivety, we will call the WML returns conditional on high-*SPFT* stocks "enhanced momentum."

If we take a closer look, part of enhanced momemtum is driven by the loser stocks in high *SPFT* quintile, showed in the top-right corner of Panel C. In comparison, in the low *SPFT* quintile, loser stocks have very comparable returns to winner stocks. This could indicate that our enhanced momentum works mainly through the selling pressure on the loser stocks, while the losers stocks in the low *SPFT* quintile exhibit remarkably strong reversal. One interpretation is that these negative returns associated with past losers are driven by fires sales (Coval and Stafford 2007). We show below that this is unlikely to be the case: first, enhanced momentum is driven both winners and losers after controlling for Fama-French three factors; and second, it is more pronounced among large stocks, which mitigates the concern about liquidity issues such as fire sales.

Fama-French alpha. After presenting raw portfolio returns, we next regress them on Fama-Frech three factors (Fama and French 1993) to control for exposure to the market, size and value factors. The resulting alphas, as well as the respective t-stats, are shown in Panel D of Table 7.[9] The alpha evidence is in line with evidence from raw returns: the WML alpha increases monotonically in $SPFT$; the difference in alpha between the top and bottom $SPFT$ quintiles is 6.2% per year, with a similar magnitude as before.

Interestingly, compared to the low $SPFT$ quintile, the high $SPFT$ quintile now exhibits both a higher winner alpha *and* a lower loser alpha. This means that, after controlling for these common factors, enhenced momentum is driven by both winners and losers, not by losers alone. It is also worth nothing that return reversal is completely subsumed by the three Fama-French factors: the low-$SPFT$ losers now on average earn a negative alpha of -1.44%, which is not statistically significant.

Regression analysis. The baseline results using sorted portfolio can be considered as a non-parametric way to estimate the effect of positive feedback trading on stock returns. To directly isolate the effect of $SPFT$ on the cross-sectional momentum strategy, we next run stock-level panel regressions of one quarter ahead returns on current quarter's $SPFT$, past 1-year return, their interaction term and a number of control variables.

$$r_{i,q+1} = a_t + \gamma_1 SPFT_{i,q} + \gamma_2 r_{i,q-4\to q} + \gamma_3 r_{i,q-4\to q} \times SPFT_{i,q} + \text{Controls}_{i,q} + \epsilon_{i,q+1} \tag{9}$$

Our coefficient of interest is γ_3. By the same logic of the previous subsections, we should expect $\gamma_3 > 0$, i.e. $SPFT$ shall amplify the effect of prior returns on the subsequent returns. In order to closely relate to previous value-weighted baseline results using portfolios, in the panel regressions in each quarter we weight the stocks by the most recent market equities. We add time fixed effect to every specification to control for time variation in the aggregate stock returns as we are interested in the cross-sectional return dispersions. We double cluster the standard error by firm and quarter.

[9]We choose not to use the four-factor model of Carhart (1997), because we are trying to explain momentum, and including the momentum factor itself could complicate our interpretation. Results are similar under this specification and available upon request.

Table 8 reports results from panel regressions with standard errors in the parentheses. Column 1 is the baseline regression containing no control variables. Here, $\hat{\gamma}_3$ equals 0.03 and is significant at 5% level. With a one-standard-deviation increase in $SPFT$ and a past one-year return of 50%, a stock will earn 1.5% (un-annualized) higher return in the subsequent quarter. Column 2 adds a number of common stock characteristics that are known to predict the future returns, namely book-to-market ratio ($BEME$), CAPM beta estimated using 5-year rolling regressions (β), total volatilities ($TVOL$), net issuance (NI), operating profit (OP), investment (INV). γ_3 coefficient does not change and maintain the same significance. As a result, the panel regression results lend additional support to the previous portfolio level results.

3.3 Subsample analysis

In this section, we discuss the robustness of enhanced momentum subsamples split in a number of ways. In Table 9, we collect the results using four sets of sample splits. To save space, the table only reports the annualized quarterly returns of winner and loser portfolios with different levels of $SPFT$. Panel A and B compare full sample with the sample excluding the 2008-09 financial crisis. The performances of enhanced momentum from Panel B are largely similar, if not better, suggesting that the financial crisis and the subsequent episode of momentum crashes, documented by Daniel and Moskowitz (2017), do not affect our results.

Panel C and D split the sample evenly in time and exclude the financial crisis in the latter half. Enhanced momentum is substantially stronger in the first half of the sample and weaker in the second half: in the first half, the return difference between high-$SPFT$ and low-$SPFT$ quintiles is 15.3%; in the second half, the difference is reduced to 2.6%. The weaker results in the second half of the sample coincide with the weak performance of momentum strategy itself: during this period of time, the unconditional momentum produces an annualized return of 3.3%. We leave it for future research to explore why momentum has decreased so much over the last two decades.

Panel E and F split the sample by the size of the stocks at each quarter, where small stocks are defined by a market capitalization below the median and large stocks by a market capitalization above the median. It turns out that enhanced momentum is almost entirely driven by large stocks: the high-$SPFT$ WML strategy delivers similar returns to the unconditional one among small stocks. This subsample analysis is interesting in several regards. First, it shows that our results are not driven by issues often associated with small stocks, such as illiquidity, stale prices, non-synchronous trading or other micro-structure issues. It also mitigates the concern associated with fire sales driving enhanced momentum. Second, the result is consistent with the evidence in Lou (2012) and Lou and Polk (2013), where they show, respectively, that flow-induced trading and arbitrage capital have a stronger impact on prices among larger stocks. While our mechanism is distinctive from their mechanisms, all three papers focus on institutional investors, whose behavior can arguably exert a bigger impact on larger stocks.

Panel G and H split the sample by the mutual fund ownership. There does not seem to be significant differences between the portfolios with high and low mutual fund ownership. Previously studies have found that higher mutual fund ownership is associated with higher price increase (Gompers and Metrick 2001) and dampened mispricing due to the increased supply of stock for short-sales (Nagel 2005). However, these effects do not seem to play a role in explaining the stronger momentum return in high-$SPFT$ stocks.

Table 10 splits the sample based on how active a fund is. Specifically, we classify funds into active funds, enhanced index funds, and pure index funds, and then compare their differential impacts on enhanced momentum. We find that $SPFT$ leads to enhanced momentum primarily through active funds and enhanced index funds, and enhanced momentum is virtually non-existent for pure index funds. This result is consistent with active trading having a larger impact on stock prices than passive holding.

3.4 Alternative measures

One may wonder about the results under alternatively defined $SPFT$ measures. In Table 11, Panel A, B, C respectively replicate the portfolio sorting exercise using weight-based *SPFT2*, Grinblatt et al. (1995)'s momentum measure *SPFT3* and time-varying momentum factor loading measure *SPFT4*, and tabulate the value-weighted average returns for the 25 independently sorted portfolios. Comparing with the baseline results, *SPFT4* delivers marginally stronger enhanced momentum, whereas weight-based *SPFT2* generates marginally weaker enhanced momentum. Surprisingly, with Grinblatt et al. (1995)'s momentum measure *SPFT*3, we do not obtain an enhanced momentum: high-*SPFT3* stocks exhibit slightly weaker momentum than low-*SPFT3* stocks. In sum, the three regression-based measures all produce similar results, whereas the one arithmetic-based measure does not.

3.5 Reversal

In this section, we present the second main result of our paper: enhanced momentum is almost fully reversed in the second quarter after formation. Table 12 shows the post-formation quarterly returns for the low-$SPFT$ and high-$SPFT$ WML portfolios from quarter 1, the quarter right after formation, to quarter 8. While the low-$SPFT$ WML strategy *underperforms* the high-$SPFT$ WML strategy by 1.8% (annualized to 7.3%), this difference is almost entirely washed away in the next quarter: the low-$SPFT$ WML strategy outperforms the high-$SPFT$ WML strategy by 1.4%. As we discuss below in Section 4, such a quick reversal is consistent with and strongly supports our price pressure mechanism. It is also worth nothing that the two-year cumulative returns are almost identical for the low-$SPFT$ and high-$SPFT$ WML strategies. This suggests that from an ex-post point of view, the two WML portfolios share very similar characteristics. At minimum, the abnormal returns of the high-$SPFT$ WML portfolio are unlikely driven by better fundamentals; otherwise these abnormal returns should persist rather than reverse.

4 Discussions

4.1 Mechanisms

While we motivate our empirical exercise using the price pressure from positive feedback trading, a number of other mechanisms may also account for our enhanced momentum. In this section, we discuss a number of these mechanisms and argue that none of them can fully explain our results.

Pre-formation stock characteristics. The first alternative mechanism is that enhanced momentum is driven by some other stock characteristics. While in the previous section we have examined Fama-French three factors, we now broaden the set of variables. In particular, we look at past one-year returns, $SPFT$, mutual fund ownership, beta, size, book-to-market ratio, idiosyncratic volatility, operating profit, investment, and net issuance. Column (2) in Panel A of Table 8 directly controls for these stock characteristics in a regression framework and shows that the explanatory power of $SPFT$ for future stock returns remains with these controls.

Furthermore, to capture these stock characteristics in a non-parametric way, Table 13 reports the average values for the five WML portfolios. The first three variables, showed in Panel A to C, are directly related to our positive feedback trading mechanism. For instance, we want to make sure that all winner portfolios have similar past one-year returns, so that their difference in returns are not driven by some winner portfolios having more extreme returns than others. By the virtue of independent sorting, the five portfolios have similar past returns and $SPFT$, and they also share a similar level of mutual fund ownership (with the exception of the low-$SPFT$ portfolio, which has a lower MF ownership). The next three variables, shown in Panel D to F, are directly from the Fama-French three factor model, which, as we discussed above, does not drive away our results.

Panel G concerns idiosyncratic volatility. While the high-$SPFT$ portfolio exhibits a lower level of idiosyncratic volatility, the magnitude is so small that it is unlikely to drive our results. Panel H concerns operating profits. Because there is a similar monotonic relationship, we resort to the regression results in Column 2 of Table 8: controlling for operating profits do not change our results. Panel I and J concern investment and net issuance, respectively, and both variables are very similar across the five portfolios.

Stock selection. A second alternative mechanism that can potentially drive our results is "stock selection," that is, positive feedback funds are able to select stocks that exhibit higher momentum. This mechanism, instead of interpreting the enhanced momentum as driven by price pressure, suggests that it could be simply a manifestation of some mechanical matching between our measure of positive feedback trading and subsequent stock returns.

Underlying this stock selection mechanism are two possible sources of matching. The first one is skill: high positive feedback funds are more skilled, so they are able to select the high-momentum stocks. One result that directly casts doubt on this mechanism is the weak, if not negative, relationship between fund returns and PFT. If, indeed, positive feedback traders are better at selecting stocks, this should show up by them having better returns. However, in Table 6, past one-year fund returns and fund flows negatively predict $SPFT$, suggesting a speculative component associated with positive feedback trading. In Table 18, which we discuss in the next section, we find no significant difference in future fund returns between high-PFT funds and low-PFT funds. Taken together, these results contradict a skill-based selection story.

The second source of matching between PFT and subsequent returns is information: positive feedback traders buy winner stocks precisely when they have some positive private information about these stocks. Under this hypothesis, the superior performance of high-$SPFT$ winners is justified by better fundamentals in subsequent periods. Our result on return reversal, as discussed in Section 3.5, directly rejects this hypothesis: if this is driven by fundamentals, then the return difference should be permanent rather than temporary. Moreover, in Table 14, we compare the post-formation fundamentals for the five WML portfolios. Specifically, we look at earnings surprises and cumulative abnormal returns during earnings announcement. Overall, these variables exhibit little variation, again casting doubt on the notion that private information is driving our results. Indeed, as shown in Panel B of Table 8, our results are robust to the inclusion of post-formation fundamentals.

Finally, there is a concern that, we, as econometricians, have by "chance" selected a fixed set of stocks with high momentum. We rule out the possibility in untabulated results by showing that there is substantial turnover for each of the 25 portfolios over time. On average, less than 15% of the stocks will remain in the same portfolio as in the last quarter, suggesting substantial transition across different portfolios.

Flow-induced trading. Lou (2012) shows that flow-induced trading, that is, the passive increase or decrease in holdings resulting from fund flows, has large explanatory power for momentum, as well as a number of other facts about mutual funds. If high-$SPFT$ winners are associated with more inflows and low-$SPFT$ losers are associated with more outflows, then our enhanced momentum could instead be driven by flow-induced trading. To alleviate this concern, Table 16 compares the flow-induced trading across the 25 different portfolios, and in particular, the flow-induced trading for low-$SPFT$ and high-$SPFT$ WML portfolios. Flow-induced trading is rather similar across the five different WML portfolios, suggesting that it is unlikely to drive our results.

Herding. Finally, we address the concern that enhanced momentum is driven by mutual fund herding. Wermers (1999) shows that stocks with large increase in mutual fund ownership in the recent quarter tend to outperform subsequently. In another paper, Dasgupta, Prat, and Verardo (2011) shows that stocks with persistent increase in mutual fund ownership tend to underperform subsequently.

To begin with, we want to point out that the two mechanisms are not mutually exclusive. In fact, as hinted by Wermers (1999), positive feedback trading can be thought of as an important source of herding: driven by a common signal, that is, past stock returns, positive feedback traders herd as rush into buying past winners and selling past losers. Indeed, Table 17 shows the percentage change in mutual fund holdings in the quarter right before formation. In Table 17, high-$SPFT$ winners experience a greater increase in mutual fund holdings, whereas low-$SPFT$ experience a smaller increase. Therefore, it is likely that positive feedback traders have been increasing their positions in winner stocks and decreasing their positions in loser stocks.

While our mechanism can lead to a particular form of herding, our empirical analysis reveals a number of significant deviations from the results in Wermers (1999). First, enhanced momentum is short-lived and almost fully reversed in the next quarter, which is consistent with our price pressure story. In comparison, the herding result in Wermers (1999) are permanent and more consistent with an information story. Second, enhanced momentum is more pronounced among large stocks, consistent with institutional investors' preference for large stocks. In comparison, in Wermers (1999), the price impact of herding is more pronounced among small stocks, again more consistent with an information-based explanation.

4.2 Fund performances

Finally, we explore the implications of our measure of positive feedback trading for fund performance. We deploy several measures of fund performance: 1) fund gross returns; 2) CAPM, Fama-French-Carhart four-factor alphas[10], which we estimate each quarter using daily returns within that quarter[11]; and 3) return gap, defined as the difference between the reported fund return and the return on a portfolio that passively invests in the disclosed fund holdings in the previous quarter, and holdings returns, which is the difference between gross return and return gap (Kacperczyk, Sialm, and Zheng 2008). The choice of return gap is driven by the fact that fund's active positive feedback trading matters predominantly for stocks newly bought or sold each quarter, and less so for stocks that passively stay in the fund's portfolio. Return gap captures the return difference between the newly bought and sold stocks within each quarter. Funds that actively engage in positive feedback trading make transactions responding strongly to stocks' past returns and these stocks are also more subject to the collective price pressure from all like-minded funds, suggesting that high PFT is associated with higher subsequent return gap.

We run panel regressions of one-quarter-ahead fund performances on PFT and a number of fund level control variables at the quarterly frequency and include time fixed effect to control for the time-varying common movement in fund performances. The standard errors are double-clustered at fund and time level. Table 18 collects the regression results that use PFT to predict five types of future fund performance. We find that, on average, high-PFT funds exhibit similar performance to low-PFT funds regarding future gross returns, factor-adjusted alphas and holdings returns as the coefficients on PFT in these regressions are all statistically indistinguishable from zero. However, when using future return gap which captures the fund return component that is actively managed as the dependent variable, we find, in columns (7) and (8), that high-PFT funds have significantly higher return gap. The positive relationship between PFT and subsequent return gap indicates that the stocks

[10]We omit Fama-French three-factor in subsequent analysis because the results are similar to the use of Fama-French-Carhart four-factor alphas.

[11]As we have shown, the price pressure from mutual fund positive feedback trading is short-lived. Estimating the alphas using high frequency (daily) observations is more appropriate for the analysis of PFT's impact on fund performance since this approach spares us the embedded high persistence from overlapping rolling regressions that are typically used in the mutual fund literature.

bought by the high-PFT fund tend to have a higher return than the stocks sold by it. The predictability is economically meaningful. One standard deviation increase in PFT increases the subsequent return gap by 2% (or 8% annualized), which 1.5 times the standard deviation of return gap. The results are robust to a battery of fund characteristics such as fund size, past one-year return, flow, etc. *ActiveShare*, notably capturing the active stock selection of funds, predicts future gross and holdings returns and factor-adjusted alphas positively but has no predictive power over the return gap.

In Table 19 we take one step further to evaluate longer-term impact of PFT on the future return gaps by extending the same regressions in column (8) of Table 18 up to eight quarters. As we have shown in the previous section, PFT is reasonably persistent at fund level from quarter to quarter. Hence high PFT funds are likely to produce positive return gaps at longer horizons, as we have found in Table 19. The last two columns use one- and two-year cumulative return gaps as dependent variables where the coefficients are 2.5 and 4 times higher than the one-quarter estimate respectively. This evidence indicates that the persistence in PFT contribute to the persistence in future return gaps. Kacperczyk, Sialm, and Zheng (2008) document strong persistence of return gap up to five years, and we complement the previous results by pointing out that mutual fund's positive feedback trading could be a viable source of the persistence.

5 Conclusion

In this paper, we examine the extent to which mutual funds' positive feedback trading drives stock price dynamics. Using mutual fund holdings data, we show that mutual funds contribute to cross-sectional momentum and excess volatility through positive feedback trading. Specifically, stocks held by positive feedback funds exhibit much stronger momentum, almost doubling the returns from a simple momentum strategy. This "enhanced" momentum is robust to alternative measures of positive feedback trading and cannot be explained by other stock characteristics, ex-post firm fundamentals, fund flows, or herding. Moreover, we show that enhanced momentum is almost fully reversed after one quarter, suggesting initial overshooting and subsequent reversal.

Our work empirically examines models of positive feedback traders such as Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), and Hong and Stein (1999), and more recently, Barberis et al. (2015). These models highlight how positive feedback trading is responsible for generating momentum and reversal. Our results also echo the point by Stein (2009) that the "institutionalization" of financial markets does not necessarily make them more efficient. Finally, although our results do not fully explain momentum, we highlight an important perspective to resolving momentum is through the lens of positive feedback trading.

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Year	Panel A: our sample			Panel B: Lou (2012)'s sample		
	# of Funds	TNA ($ Millions)		# of Funds	TNA ($ Millions)	
		Mean	Median		Mean	Median
1980	189	166.88	61.37	228	146.74	53.45
1981	181	184.22	64.82	226	137.71	53.66
1982	171	187.18	70.61	232	170.95	53.66
1983	211	242.87	104.13	255	222.14	97.41
1984	222	262.36	114.16	270	221.24	86.23
1985	250	280.87	109.13	297	275.98	114.12
1986	291	309.40	125.27	341	298.47	106.42
1987	365	341.79	98.12	376	286.30	87.00
1988	411	299.93	82.52	405	285.34	82.47
1989	457	322.03	83.98	440	340.49	95.08
1990	425	322.92	83.80	480	306.07	83.85
1991	582	364.15	92.52	579	379.32	100.23
1992	639	407.66	98.52	685	426.04	115.22
1993	814	426.18	109.26	925	442.40	105.56
1994	972	420.50	100.34	1,044	450.12	105.43
1995	1,159	610.30	124.37	1,168	610.98	134.35
1996	1,264	787.18	157.26	1,314	750.48	145.88
1997	1,520	951.06	157.49	1,480	933.60	163.42
1998	1,714	1,103.96	164.50	1,570	1,071.47	167.00
1999	1,943	1,173.27	144.88	1,686	1,307.48	187.52
2000	2,214	1,319.00	172.87	1,890	1,283.93	186.27
2001	2,054	827.41	123.45	1,915	1,018.79	155.22
2002	2,642	788.19	120.18	1,970	771.11	111.80
2003	2,704	789.68	125.35	2,001	976.25	146.05
2004	2,587	989.65	165.75	1,961	1,128.54	165.93
2005	2,547	1,136.61	182.75	1,918	1,251.72	196.90
2006	2,390	1,235.55	216.25	1,789	1,400.29	221.75
2007	2,600	1,260.52	205.73			
2008	2,426	996.68	143.81			
2009	2,546	964.01	143.25			
2010	3,405	1,299.52	231.00			
2011	3,934	1,721.76	282.40			
2012	3,729	1,855.43	306.40			
2013	3,460	2,288.23	391.93			
2014	2,041	2,667.60	463.95			

Table 1: Summary statistics for the mutual fund sample

Note: This table reports summary statistics of the mutual fund sample in each year. The sample period is from 1980 to 2014. International, fixed income, and precious metal funds are excluded. Fund size, monthly returns, and capital flows are obtained from the CRSP survivorship-bias-free mutual fund database, and fund holdings data are from the Thompson Financial's CDA/Spectrum database. The two data sets are then merged using the MFLinks file provided on WRDS. # of funds is the number of actively managed equity mutual funds at the end of each year; TNA is the total net assets under management reported by CRSP (in millions of dollars).

						Panel B: correlation matrix			
	p25	median	p75	mean	obs.	PFT	$PFT2$	$PFT3$	$PFT4$
PFT	-0.13	0.13	0.69	0.28	144,150	1.00			
$PFT2$	-0.23	0.00	0.17	-0.05	144,150	0.57	1.00		
$PFT3$	-0.39	-0.01	0.36	0.00	144,150	0.45	0.56	1.00	
$PFT4$	-0.49	0.01	0.53	0.05	144,150	0.14	0.09	0.09	1.00

Table 2: Summary statistics for different PFT measures

Note: This table reports distribution properties and correlation matrix of the four positive feedback trading (PFT) measures constructed in Section 2. The sample period is from 1980 to 2014. PFT is estimated by regressing adjusted holdings change on past one-year stock returns. $PFT2$ is estimated by regressing the adjusted change in portfolio weights on past one-year stock returns. $PFT3$ is the Grinblatt, Titman, and Wermers (1995) measure based on past one-year stock returns and changes in portfolio weights. $PFT4$ is estimated as the loading on the momentum factor using the Fama-French-Carhart model with a 5-year rolling window.

	Panel A: PFT				Panel B: $PFT2$ to $PFT4$		
	average	median	std.dev.	obs.	$PFT2$	$PFT3$	$PFT4$
International	0.29	0.11	1.07	6,335	-0.02	0.01	-0.03
Aggressive Growth	0.38	0.21	0.86	10,917	0.01	0.09	0.32
Growth	0.31	0.15	0.98	55,999	-0.04	0.00	0.05
Growth & Income	0.24	0.11	1.07	17,990	-0.12	-0.04	-0.21
Balanced	0.30	0.15	1.02	1,007	-0.08	0.03	-0.08
Total	0.30	0.15	0.99	92,248	-0.05	0.01	0.02

Table 3: Summary statistics of PFT measures by investment objectives

Note: This table reports summary statistics of PFT measures classified by the investment objective code obtain from CRSP Mutual Fund database. We restrict the sample to the observations that contain valid IOC codes; we dropped unclassified funds in reporting these statistics. The sample period is from 1980 to 2014. PFT is estimated by regressing adjusted holdings change on past one-year stock returns. $PFT2$ is estimated by regressing the adjusted change in portfolio weights on past one-year stock returns. $PFT3$ is the Grinblatt, Titman, and Wermers (1995) measure based on past one-year stock returns and changes in portfolio weights. $PFT4$ is estimated as the loading on the momentum factor using the Fama-French-Carhart model with a 5-year rolling window.

	$PFT_{(q)}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$PFT_{(q-1)}$	0.19***					0.12***	0.11***
	(0.01)					(0.00)	(0.01)
$PFT_{(q-2)}$		0.19***				0.12***	0.09***
		(0.01)				(0.00)	(0.01)
$PFT_{(q-3)}$			0.16***			0.08***	0.06***
			(0.01)			(0.00)	(0.01)
$PFT_{(q-4)}$				0.19***		0.12***	0.09***
				(0.01)		(0.00)	(0.01)
$PFT_{(q-5)}$					0.14***	0.06***	0.04***
					(0.01)	(0.00)	(0.01)
$PFT_{(q-6)}$							0.06***
							(0.01)
$PFT_{(q-7)}$							0.04***
							(0.00)
$PFT_{(q-8)}$							0.06***
							(0.01)
$PFT_{(q-9)}$							0.04***
							(0.01)
$PFT_{(q-10)}$							0.05***
							(0.01)
Time FE	✓	✓	✓	✓	✓	✓	✓
Obs.	131,040	119,980	110,866	106,654	102,681	93,937	64,074
R^2	0.06	0.06	0.05	0.06	0.04	0.11	0.13

Table 4: Persistence of mutual fund positive feedback trading PFT

Note: This table examines the persistence of mutual fund positive feedback trading PFT with time fixed effect panel regressions. The sample period is from 1980 to 2014. International, fixed income, and precious metal funds are excluded. For each fund, PFT in quarter q is estimated as the coefficient of regressing the adjusted share changes in each stock position on that stock's past one-year return. All standard errors are double-clustered by fund and quarter. *p<0.1; **p<0.05; ***p<0.01.

Panel A: Quarterly transition probability

	1	2	3	4	5
1	33%	20%	15%	16%	16%
2	20%	23%	22%	18%	17%
3	16%	22%	26%	20%	16%
4	16%	19%	20%	25%	20%
5	15%	16%	16%	21%	31%

Panel B: Annual transition probability

	1	2	3	4	5
1	42%	20%	15%	13%	11%
2	29%	30%	23%	16%	12%
3	14%	23%	28%	21%	14%
4	12%	15%	22%	28%	23%
5	11%	11%	14%	24%	40%

Table 5: Quarterly and annual transition probability matrix of mutual fund style

Note: The table reports the transition probability matrices of a mutual fund moving from one quantile of the cross-sectional distribution of PFT to another quantile in the following period. Panel A uses quarterly PFT and Panel B uses annual four-quarter average PFT to calculate the transition matrices. The sample period is from 1980 to 2014.

	Dependent variable: PFT						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Active	0.16***				0.17***	0.17***	0.22***
	(0.02)				(0.03)	(0.03)	(0.04)
1yr MOM return		0.32***			0.24***	0.19***	0.15**
		(0.09)			(0.08)	(0.06)	(0.06)
1yr fund return			-0.36***		-0.29***	-0.12**	-0.14**
			(0.06)		(0.05)	(0.05)	(0.06)
1yr fund flow				-0.01**	-0.01***	-0.02***	-0.01**
				(0.01)	(0.01)	(0.01)	(0.01)
TNA					0.04**	0.04**	0.05**
					(0.02)	(0.02)	(0.02)
TNA^2					-0.00***	-0.00***	-0.01***
					(0.00)	(0.00)	(0.00)
Turnover					0.02***	0.02***	0.02***
					(0.01)	(0.01)	(0.01)
Expense ratio					-5.62***	-5.32***	-0.44
					(1.65)	(1.72)	(2.11)
1yr MKT return						-0.20***	-0.21***
						(0.07)	(0.08)
1yr SMB return						-0.48***	-0.47***
						(0.14)	(0.15)
1yr HML return						-0.01	-0.00
						(0.09)	(0.09)
Active Share							-0.20***
							(0.04)
Management fee							-0.08**
							(0.03)
IOC FE	✓	✓	✓	✓	✓	✓	✓
Observations	112,295	112,295	112,295	112,295	110,136	110,136	91,997
R^2	0.00	0.01	0.01	0.00	0.01	0.02	0.02

Table 6: Determinants of mutual fund PFT

Note: This table reports results from panel regressions that regress mutual fund PFT on a number of explanatory variables of fund characteristics and aggregate factor returns at quarterly frequency. For each fund, PFT in quarter q is estimated as the coefficient of regressing the adjusted share changes in each stock position on that stock's past one-year return. Active is a dummy variable for active funds. 1yr MOM (MKT, SMB, HML) return is the return from the MOM (MKT, SMB, HML) factor in the previous year. 1yr fund return (flow) is the return (flow) for the fund in the previous year. TNA is the total net asset (in millions). Active Share is the active share measure from Cremers and Petajisto (2009). Standard errors (in parentheses) are double-clustered by fund and quarter. *** p<0.01, ** p<0.05, * p<0.1

Panel A: Mutual fund ownership changes

		Low-SPFT 1	2	3	4	High-SPFT 5
Loser	**1**	3.40%	3.23%	2.80%	2.99%	3.08%
	2	3.67%	3.50%	3.33%	3.26%	3.57%
	3	3.49%	3.47%	3.61%	3.81%	3.96%
	4	3.82%	4.30%	4.09%	4.69%	5.49%
Winner	**5**	5.02%	6.31%	7.76%	8.29%	8.37%
WML		**1.61%**	**3.09%**	**4.96%**	**5.30%**	**5.29%**

Panel B: Number of stocks in each portfolio

		Low-SPFT 1	2	3	4	High-SPFT 5
Loser	**1**	120	112	101	86	67
	2	119	104	97	88	79
	3	103	100	96	93	95
	4	85	91	95	104	111
Winner	**5**	59	79	98	116	135

Panel C: Portfolio returns (annualized)

		Low-SPFT 1	2	3	4	High-SPFT 5	H-L
Loser	**1**	12.45%	8.99%	7.90%	8.76%	5.19%	
		(2.81)	(1.99)	(1.79)	(1.88)	(1.09)	
	2	12.37%	13.18%	13.12%	10.18%	10.28%	
		(3.68)	(4.13)	(3.83)	(2.93)	(2.93)	
	3	11.78%	13.16%	12.84%	11.63%	9.40%	
		(4.13)	(4.34)	(4.34)	(3.86)	(2.81)	
	4	13.85%	14.74%	12.60%	13.12%	13.81%	
		(4.92)	(5.08)	(4.40)	(4.41)	(4.23)	
Winner	**5**	15.43%	13.14%	13.10%	14.91%	15.46%	
		(4.32)	(3.25)	(3.31)	(3.40)	(3.55)	
WML		**2.98%**	**4.15%**	**5.20%**	**6.16%**	**10.26%**	**7.28%**
		(0.80)	(1.02)	(1.47)	(1.41)	(2.54)	(2.19)

Panel D: Fama-Frech alpha

		Low-SPFT 1	2	3	4	High-SPFT 5
Loser	**1**	-1.44%	-4.32%	-5.34%	-3.93%	-5.96%
		(-0.52)	(-1.57)	(-2.29)	(-1.49)	(-2.14)
	2	0.36%	2.09%	0.76%	-1.07%	0.12%
		(0.22)	(1.28)	(0.45)	(-0.70)	(0.07)
	3	0.99%	2.24%	2.89%	2.26%	-0.39%
		(0.82)	(1.47)	(1.93)	(1.41)	(-0.27)
	4	3.80%	4.67%	3.04%	3.90%	5.16%
		(2.77)	(3.10)	(2.18)	(2.64)	(3.82)
Winner	**5**	5.53%	4.01%	2.86%	5.66%	7.17%
		(2.69)	(1.74)	(1.40)	(2.26)	(3.44)
WML		**6.97%**	**8.33%**	**8.20%**	**9.60%**	**13.13%**
		(1.83)	(2.01)	(2.20)	(2.11)	(3.31)

Table 7: Ownership changes and returns for stocks sorted by $SPFT$ and past returns

Note: Stocks are independently sorted by past one-year returns and the most recent $SPFT$ at each quarter. $SPFT$ is computed by aggregating fund PFT to stock level. Panel A, B, C, D tabulate in each portfolio, respectively, value-weighted percentage changes in mutual fund ownership, average number of stocks, value-weighted annualized subsequent quarterly returns, and Fama-French three-factor alphas. In Panel C and D, t-statistics are reported in the parentheses. The sample period is from 1980 to 2014.

	Dependent variable: $r_{i,q+1}$				
	Panel A: Pre-formation		Panel B: Post-formation		
	(1)	(2)	(3)	(4)	(5)
$PFT_{i,q} \times r_{i,q-4,q}$	0.03**	0.03**	0.06***	0.06***	0.04**
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
$r_{i,q-4,q}$	0.00	0.00	-0.01	-0.01	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$PFT_{i,q}$	-0.43	0.01	-0.48	-0.47	-0.01
	(0.40)	(0.38)	(0.47)	(0.47)	(0.40)
$BEME_{i,q}$		1.01**	1.23*	1.15*	1.11**
		(0.44)	(0.62)	(0.62)	(0.55)
$\beta_{i,q}$		0.04	0.15	0.16	0.09
		(0.92)	(1.08)	(1.07)	(0.96)
$TVOL_{i,q}$		-42.55	-5.10	-17.01	-27.94
		(35.80)	(42.55)	(40.53)	(36.79)
$NI_{i,q}$		-1.00***	-0.66*	-0.81**	-1.10***
		(0.35)	(0.39)	(0.38)	(0.37)
$OP_{i,q}$		0.57**	0.43	0.56	0.54
		(0.28)	(0.35)	(0.35)	(0.35)
$INV_{i,q}$		-1.02**	-1.38***	-1.27***	-1.15**
		(0.39)	(0.48)	(0.48)	(0.44)
$ACT_{i,q+1}$			0.55**		
			(0.23)		
$SUE_{i,q+1}$				42.56***	
				(8.44)	
$CAR_{i,q+1}$					-3.62
					(2.20)
Time FE	✓	✓	✓	✓	✓
Obs	310,803	252,098	167,557	167,557	212,995
R^2	0.28	0.28	0.28	0.28	0.28

Table 8: Panel regressions of future stock returns on $SPFT$

Note: In each quarter, the observations are weighted by the most recent market equities. Standard errors clustered by time and firm are reported in the parentheses. The control variables include book-to-market ratio ($BEME$), CAPM beta estimated using 5-year rolling regressions (β), total volatilities ($TVOL$), net issuance (NI), operating profit (OP), investment (INV), ex-post actual earnings announcement (ACT), ex-post earnings surprises to analyst forecasts (SUR) and ex-post earnings announcement two-day window cumulative abnormal return. The sample period is from 1980 to 2014.

	Panel A: Full sample					Panel B: Full sample, exlc. crisis				
	SPFT(Low)	**2**	**3**	**4**	**SPFT(High)**	**SPFT(Low)**	**2**	**3**	**4**	**SPFT(High)**
Loser	12.45%	8.99%	7.90%	8.76%	5.19%	13.85%	10.45%	8.97%	9.77%	5.80%
Winner	15.43%	13.14%	13.10%	14.91%	15.46%	15.97%	15.23%	15.24%	17.36%	17.43%
W-L	**2.98%**	**4.15%**	**5.20%**	**6.16%**	**10.26%**	**2.12%**	**4.78%**	**6.27%**	**7.58%**	**11.64%**

	Panel C: Before 1998					Panel D: After 1998, excl. crisis				
	SPFT(Low)	**2**	**3**	**4**	**SPFT(High)**	**SPFT(Low)**	**2**	**3**	**4**	**SPFT(High)**
Loser	13.09%	9.83%	8.63%	9.20%	4.50%	14.76%	11.20%	9.39%	10.46%	7.36%
Winner	14.76%	17.17%	17.25%	20.22%	21.44%	17.44%	12.88%	12.82%	13.90%	12.60%
W-L	**1.66%**	**7.34%**	**8.62%**	**11.02%**	**16.94%**	**2.68%**	**1.69%**	**3.43%**	**3.43%**	**5.24%**

	Panel E: Small stocks					Panel F: Big stocks				
	SPFT(Low)	**2**	**3**	**4**	**SPFT(High)**	**SPFT(Low)**	**2**	**3**	**4**	**SPFT(High)**
Loser	9.58%	4.51%	5.48%	4.19%	5.31%	11.28%	8.63%	11.46%	8.62%	5.70%
Winner	17.97%	21.48%	19.35%	16.12%	16.14%	15.86%	12.29%	12.92%	16.72%	15.03%
W-L	**8.39%**	**16.97%**	**13.86%**	**11.92%**	**10.83%**	**4.58%**	**3.66%**	**1.46%**	**8.10%**	**9.33%**

	Panel G: Low MF ownership					Panel H: High MF ownership				
	SPFT(Low)	**2**	**3**	**4**	**SPFT(High)**	**SPFT(Low)**	**2**	**3**	**4**	**SPFT(High)**
Loser	10.73%	8.44%	7.28%	8.27%	4.26%	14.04%	6.71%	7.41%	7.60%	7.85%
Winner	15.12%	13.09%	11.90%	11.21%	13.80%	18.32%	14.19%	14.79%	14.89%	17.30%
W-L	**4.39%**	**4.64%**	**4.63%**	**2.93%**	**9.55%**	**4.28%**	**7.48%**	**7.39%**	**7.29%**	**9.45%**

Table 9: Portfolio returns of stocks sorted by $SPFT$ and past returns in various subsamples

Note: Stocks are independently sorted by past one-year returns and the most recent $SPFT$ at each quarter. $SPFT$ is computed by aggregating fund PFT to stock level. We consider four set of sample splits: including/excluding financial crisis, before/after 1998, big/small stocks, and high/low mutual fund ownership. The table only reports the annualized quarterly returns of winner and loser portfolios with different levels of $SPFT$. The sample period is from 1980 to 2014.

		Low-SPFT				High-SPFT
		1	**2**	**3**	**4**	**5**
		Panel A: SPFT based on active funds				
Loser	**1**	12.02%	9.56%	6.92%	8.62%	5.98%
	2	12.76%	13.34%	14.06%	10.99%	9.48%
	3	11.37%	13.36%	12.55%	11.23%	9.87%
	4	14.04%	15.03%	12.64%	13.59%	13.31%
Winner	**5**	15.43%	14.13%	14.19%	13.78%	15.30%
W-L		**3.41%**	**4.57%**	**7.27%**	**5.15%**	**9.32%**
		Panel B: SPFT based on enhanced index funds				
Loser	**1**	12.47%	10.11%	7.32%	5.98%	6.54%
	2	14.47%	15.28%	10.10%	6.51%	11.86%
	3	13.57%	11.11%	12.27%	5.61%	10.36%
	4	12.47%	10.58%	6.85%	6.32%	12.55%
Winner	**5**	12.55%	6.75%	5.33%	10.30%	10.61%
W-L		**0.08%**	**-3.36%**	**-1.99%**	**4.32%**	**4.07%**
		Panel C: SPFT based on pure index funds				
Loser	**1**	5.91%	4.48%	9.32%	12.06%	8.91%
	2	8.77%	8.92%	8.48%	11.22%	11.93%
	3	13.52%	8.34%	9.96%	10.32%	10.96%
	4	12.81%	10.15%	12.15%	10.89%	14.06%
Winner	**5**	14.64%	12.53%	14.34%	15.14%	13.27%
W-L		**8.72%**	**8.05%**	**5.02%**	**3.08%**	**4.35%**

Table 10: Returns for stocks sorted by measures of SPFT constructed from active and passive funds

Note: Each quarter stocks are independently sorted by past one-year returns and the most recent $SPFT$ constructed from different fund types. $SPFT$ is computed by aggregating fund-level PFT among a specific fund type to stock level, using fund holdings as weights. Panel A, B, and C tabulate value-weighted annualized subsequent quarterly returns for $SPFT$ constructed from actively managed funds, enhanced index funds, and pure index funds respectively. The sample period is from 1980 to 2014.

		Low-SPFT				High-SPFT
		1	**2**	**3**	**4**	**5**
		Panel A: $SPFT2$				
Loser	**1**	10.04%	9.79%	9.42%	8.58%	5.78%
	2	12.53%	11.61%	13.04%	10.10%	11.91%
	3	11.45%	13.72%	13.02%	12.74%	8.75%
	4	14.66%	13.80%	13.72%	14.46%	14.16%
Winner	**5**	15.84%	17.28%	14.79%	12.13%	14.87%
W-L		**5.80%**	**7.49%**	**5.37%**	**3.54%**	**9.09%**
		Panel B: $SPFT3$				
Loser	**1**	9.01%	7.87%	6.48%	7.35%	5.59%
	2	11.88%	10.65%	11.14%	11.35%	11.76%
	3	12.13%	11.86%	12.87%	12.59%	9.45%
	4	14.94%	13.45%	12.92%	14.44%	13.54%
Winner	**5**	19.31%	14.71%	13.22%	13.55%	13.48%
W-L		**10.31%**	**6.84%**	**6.74%**	**6.20%**	**7.89%**
		Panel C: $SPFT4$				
Loser	**1**	10.29%	10.49%	9.42%	8.21%	4.28%
	2	13.35%	13.13%	11.68%	11.03%	7.03%
	3	12.99%	13.14%	12.01%	9.96%	7.70%
	4	14.17%	14.41%	14.67%	13.44%	11.72%
Winner	**5**	12.13%	13.94%	13.83%	15.13%	16.04%
W-L		**1.85%**	**3.45%**	**4.41%**	**6.92%**	**11.77%**

Table 11: Returns for stocks sorted by alternative measures of SPFT and past returns

Note: Stocks are independently sorted by past one-year returns and the most recent $SPFT2$ ($SPFT3$, $SPFT4$) at each quarter. $SPFT2$ ($SPFT3$, $SPFT4$) is computed by aggregating fund-level $PFT2$ ($PFT3$, $PFT4$) to stock level, using fund holdings as weights. $PFT2$ is estimated by regressing the adjusted change in portfolio weights on past one-year stock returns. $PFT3$ is the Grinblatt, Titman, and Wermers (1995) measure based on past one-year stock returns and changes in portfolio weights. $PFT4$ is estimated as the loading on the momentum factor using the Fama-French-Carhart model with a 5-year rolling window. Panel A, B, and C tabulate value-weighted annualized subsequent quarterly returns for $PFT2$, $PFT3$, and $PFT4$, respectively. The sample period is from 1980 to 2014.

Quarter	low-$SPFT$ WML	high-$SPFT$ WML	Difference
1	0.75%	2.57%	1.82%
2	2.12%	0.72%	-1.40%
3	0.68%	0.77%	0.09%
4	-0.50%	-0.21%	0.29%
5	-0.43%	0.42%	0.84%
6	0.34%	-1.67%	-2.01%
7	-1.15%	-0.58%	0.58%
8	-0.44%	-0.78%	-0.34%
Q1-Q8	**1.36%**	**1.23%**	**0.13%**
Q2-Q8	**0.62%**	**-1.34%**	**1.96%**

Table 12: Quarterly returns after formation for low-$SPFT$ and high-$SPFT$ WML portfolios
Note: The table reports the WML returns for low-$SPFT$ and high-$SPFT$ stocks for each of the eight quarters after the initial formation. Stocks are independently sorted by past one-year returns and the most recent $SPFT$ at each quarter. $SPFT$ is computed by aggregating fund PFT to stock level, using fund holdings as weights. Returns are quarterly, not annualized. The sample period is from 1980 to 2014.

	Panel A: Past 1-year returns					Panel B: PFT				
	SPFT(Low)	**2**	**3**	**4**	**SPFT(High)**	**SPFT(Low)**	**2**	**3**	**4**	**SPFT(High)**
Loser	-24.62%	-24.40%	-23.66%	-23.27%	-23.54%	-0.36	-0.01	0.16	0.35	0.66
Winner	77.94%	81.11%	83.31%	84.83%	85.17%	-0.32	0.00	0.17	0.36	0.69
W-L	**102.56%**	**105.51%**	**106.97%**	**108.09%**	**108.71%**	**0.04**	**0.01**	**0.01**	**0.01**	**0.03**

	Panel C: MF Ownership					Panel D: Size (in billions)				
	SPFT(Low)	**2**	**3**	**4**	**SPFT(High)**	**SPFT(Low)**	**2**	**3**	**4**	**SPFT(High)**
Loser	9.50%	9.04%	9.18%	9.71%	9.95%	10.07	22.95	27.88	31.40	19.85
Winner	9.45%	10.12%	10.50%	11.23%	11.38%	6.28	13.40	18.83	25.23	35.49
W-L	**-0.05%**	**1.09%**	**1.32%**	**1.52%**	**1.43%**	**-3.79**	**-9.55**	**-9.05**	**-6.17**	**15.64**

	Panel E: Book-to-market					Panel F: Market beta				
	SPFT(Low)	**2**	**3**	**4**	**SPFT(High)**	**SPFT(Low)**	**2**	**3**	**4**	**SPFT(High)**
Loser	0.89	0.76	0.63	0.52	0.47	1.03	1.09	1.13	1.20	1.23
Winner	0.59	0.51	0.42	0.33	0.25	0.92	1.03	1.10	1.20	1.25
W-L	**-0.30**	**-0.25**	**-0.21**	**-0.19**	**-0.22**	**-0.11**	**-0.06**	**-0.03**	**0.00**	**0.02**

	Panel G: Idiosyncratic volatility					Panel H: Operating profit				
	SPFT(Low)	**2**	**3**	**4**	**SPFT(High)**	**SPFT(Low)**	**2**	**3**	**4**	**SPFT(High)**
Loser	2.10%	2.08%	2.10%	2.16%	2.36%	35.80%	34.77%	37.92%	35.49%	36.23%
Winner	2.05%	2.05%	2.02%	1.97%	1.92%	29.15%	31.75%	32.43%	35.73%	36.93%
W-L	**-0.05%**	**-0.03%**	**-0.08%**	**-0.19%**	**-0.44%**	**-6.65%**	**-3.02%**	**-5.49%**	**0.24%**	**0.70%**

	Panel I: Investment					Panel J: Net issuance				
	SPFT(Low)	**2**	**3**	**4**	**SPFT(High)**	**SPFT(Low)**	**2**	**3**	**4**	**SPFT(High)**
Loser	0.18	0.26	0.29	0.34	0.41	11.26%	14.03%	16.71%	20.95%	24.60%
Winner	0.16	0.16	0.21	0.25	0.29	7.74%	8.42%	11.41%	14.57%	18.45%
W-L	**-0.02**	**-0.09**	**-0.09**	**-0.09**	**-0.11**	**-3.52%**	**-5.61%**	**-5.29%**	**-6.38%**	**-6.14%**

Table 13: Other portfolio characteristics for stocks sorted by $SPFT$ and past returns

Note: Stocks are independently sorted by past one-year returns and the most recent $SPFT$ at each quarter. $SPFT$ is computed by aggregating fund PFT to stock level. Each panel corresponds to the value-weighted stock characteristic for the ten winner and loser portfolios.

	Panel A: SUE: Analysts forecasts					Panel B: SUE: Random walk				
	SPFT(Low)	**2**	**3**	**4**	**SPFT(High)**	**SPFT(Low)**	**2**	**3**	**4**	**SPFT(High)**
Loser	-1.38%	-0.27%	-0.38%	-0.33%	-0.28%	-1.52%	-0.85%	-1.11%	-0.71%	-0.79%
Winner	0.03%	0.12%	0.00%	0.05%	0.07%	0.75%	0.61%	0.56%	0.53%	0.39%
W-L	**1.41%**	**0.39%**	**0.39%**	**0.38%**	**0.35%**	**2.27%**	**1.47%**	**1.66%**	**1.25%**	**1.18%**

	Panel C: CAR: (-1,1)					Panel D: CAR: Long term				
	SPFT(Low)	**2**	**3**	**4**	**SPFT(High)**	**SPFT(Low)**	**2**	**3**	**4**	**SPFT(High)**
Loser	-0.07%	-0.08%	-0.21%	0.10%	0.11%	-0.54%	-0.90%	-1.01%	-1.04%	-0.90%
Winner	0.19%	0.11%	0.17%	0.33%	0.24%	0.16%	-0.12%	0.69%	0.32%	0.11%
W-L	**0.26%**	**0.20%**	**0.38%**	**0.23%**	**0.13%**	**0.70%**	**0.79%**	**1.70%**	**1.36%**	**1.01%**

Table 14: Post-formation earnings surprises and cumulative abnormal returns of stocks sorted by $SPFT$ and past return

Note: Stocks are independently sorted by past one-year returns and the most recent $SPFT$ at each quarter. $SPFT$ is computed by aggregating fund PFT to stock level. Each panel corresponds to the value-weighted stock characteristic for the ten winner and loser portfolios. Panel A and B tabulate post-formation earnings surprise against median analyst forecasts and a rolling seasonal random walk model respectively. Panel C and D tabulate cumulative abnormal returns (CAR) in (-1,1) window around earnings announcement dates and over the period from two days after the announcement through one day after the following quarterly earnings announcement respectively.

		Low-SPFT 1	2	3	4	High-SPFT 5
Loser	**1**	33%	20%	15%	16%	16%
	2	20%	23%	22%	18%	17%
	3	16%	22%	26%	20%	16%
	4	16%	19%	20%	25%	20%
Winner	**5**	15%	16%	16%	21%	31%

Table 15: Portfolio rebalance

Note: Stocks are independently sorted by past one-year returns and the most recent $SPFT$ at each quarter. $SPFT$ is computed by aggregating fund PFT to stock level. Each cell shows the average fraction of stocks that remain in the same portfolio in the next period. The sample period is from 1980 to 2014.

		Low-SPFT 1	2	3	4	High-SPFT 5
Loser	**1**	0.06%	-0.01%	-0.08%	-0.18%	-0.29%
	2	0.12%	0.06%	-0.05%	-0.06%	-0.19%
	3	0.26%	0.12%	0.06%	-0.02%	-0.10%
	4	0.28%	0.23%	0.13%	0.09%	-0.10%
Winner	**5**	0.29%	0.31%	0.11%	0.26%	0.08%
WML		**0.23%**	**0.32%**	**0.19%**	**0.44%**	**0.37%**

Table 16: Flow-induced trading

Note: Stocks are independently sorted by past one-year returns and the most recent $SPFT$ at each quarter. $SPFT$ is computed by aggregating fund PFT to stock level. Each cell shows the average flow-induced trading of that portfolio, defined by the flow-induced share change divided by the total number of shares outstanding. The sample period is from 1980 to 2014.

		Low-SPFT				High-SPFT
		1	**2**	**3**	**4**	**5**
Loser	**1**	3.65%	2.99%	2.78%	2.86%	3.14%
	2	3.71%	3.22%	3.28%	3.23%	4.08%
	3	3.51%	3.94%	3.87%	4.13%	4.23%
	4	3.79%	4.18%	4.57%	5.41%	6.45%
Winner	**5**	4.89%	5.86%	6.91%	8.82%	10.90%
WML		**1.24%**	**2.86%**	**4.13%**	**5.96%**	**7.76%**

Table 17: Pre-formation mutual fund holdings change

Note: Stocks are independently sorted by past one-year returns and the most recent $SPFT$ at each quarter. $SPFT$ is computed by aggregating fund PFT to stock level. Each cell shows the average percentage change in mutual fund holdings in the quarter right before the formation. The sample period is from 1980 to 2014.

	Gross return		CAPM α		Four-factor α		Return gap		Holdings return	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
PFT	0.05	0.01	-0.04	-0.08	-0.00	-0.07	0.01**	0.02***	0.03	-0.02
	(0.06)	(0.07)	(0.09)	(0.10)	(0.04)	(0.04)	(0.01)	(0.01)	(0.06)	(0.07)
TNA	-0.19*	-0.26**	-0.08	-0.16	-0.07	-0.08	0.01	0.03	-0.27**	-0.31**
	(0.11)	(0.12)	(0.10)	(0.10)	(0.07)	(0.07)	(0.03)	(0.03)	(0.12)	(0.13)
TNA^2	0.01	0.02*	-0.00	0.01	0.00	0.00	-0.00	-0.00	0.02**	0.02**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
$rret_{t-4,t}$	1.91*	1.71	1.13	0.81	0.89*	0.65	0.37***	0.39**	1.49	1.28
	(0.99)	(1.03)	(1.19)	(1.12)	(0.53)	(0.46)	(0.14)	(0.15)	(1.00)	(1.04)
$Flow$	0.05	0.01	-0.03	-0.07	0.04	0.01	-0.02	-0.02	0.07	0.02
	(0.05)	(0.05)	(0.05)	(0.05)	(0.03)	(0.03)	(0.01)	(0.01)	(0.06)	(0.06)
$Turnover$	-0.01	-0.02	-0.09*	-0.09*	-0.12***	-0.11***	-0.00	-0.00	-0.02	-0.02
	(0.04)	(0.04)	(0.05)	(0.05)	(0.04)	(0.04)	(0.01)	(0.01)	(0.05)	(0.05)
$Expenses$	17.70	16.43	-2.22	-16.71	0.41	-1.89	-3.29	4.28*	27.46**	12.93
	(11.43)	(12.75)	(14.01)	(13.00)	(9.48)	(8.71)	(2.77)	(2.39)	(12.01)	(13.20)
$ActiveShare$		0.90**		1.29**		0.58*		-0.08		0.97**
		(0.43)		(0.62)		(0.30)		(0.08)		(0.44)
$Fees$		-0.37		-0.26		-0.19		-0.12***		-0.23
		(0.25)		(0.17)		(0.12)		(0.04)		(0.25)
Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
R^2	0.61	0.63	0.09	0.10	0.05	0.05	0.06	0.05	0.62	0.64
Obs	106,033	88,439	93,409	88,038	93,409	88,038	99,956	83,620	99,956	83,620

Table 18: PFT and one-quarter ahead mutual fund performance

Note: This table reports results from panel regressions that regress future mutual fund performance measures on PFT and a number of other explanatory variables at quarterly frequency. The dependent variables are one-quarter ahead gross returns; CAPM, Three-factor, and Four-factor αestimated using daily fund returns; and return gap as defined by Kacperczyk, Sialm, and Zheng (2008). Standard errors (in parentheses) are double-clustered by fund and quarter. Time fixed effects are added to each regression. *** p<0.01, ** p<0.05, * p<0.1.

	$ReturnGap_{t+k}$								$\sum_{i=1}^{k} ReturnGap_{t+i}$	
$k =$	1	2	3	4	5	6	7	8	4	8
PFT_t	0.02***	0.01	0.00	0.02**	0.02***	0.01	0.02**	0.00	0.05**	0.08**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.03)
TNA_t	0.03	0.02	0.03	0.04	0.05*	0.04	0.05**	0.06**	0.11	0.36**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.09)	(0.17)
TNA_t^2	-0.00	-0.00	-0.00*	-0.00**	-0.00**	-0.00**	-0.00***	-0.01***	-0.01*	-0.03**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
$rret_{t-4,t}$	0.39**	0.25**	0.25**	0.17*	0.02	0.17**	0.18**	0.16**	0.81***	1.21***
	(0.15)	(0.11)	(0.10)	(0.10)	(0.08)	(0.08)	(0.08)	(0.06)	(0.30)	(0.41)
$Flow_t$	-0.02	-0.02*	-0.02**	-0.03**	-0.04***	-0.04***	-0.05***	-0.05***	-0.08**	-0.30***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.04)	(0.06)
$Turnover_t$	-0.00	0.00	-0.00	0.00	0.01	0.01	0.01	0.01	-0.00	0.04
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.06)
$Expenses_t$	4.28*	5.63**	6.47***	6.50***	6.30***	5.78***	4.82**	4.57**	25.20***	49.85***
	(2.39)	(2.26)	(2.12)	(2.23)	(2.13)	(2.12)	(2.18)	(1.94)	(7.97)	(14.82)
$ActiveShare_t$	-0.08	-0.09	-0.10	-0.12*	-0.11*	-0.11*	-0.11*	-0.13**	-0.35	-0.60
	(0.08)	(0.08)	(0.07)	(0.07)	(0.06)	(0.06)	(0.06)	(0.06)	(0.23)	(0.37)
Fee_t	-0.12***	-0.14***	-0.15***	-0.15***	-0.17***	-0.17***	-0.15***	-0.15***	-0.53***	-1.15***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	-0.04	(0.15)	(0.27)
Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
R^2	0.05	0.04	0.04	0.03	0.03	0.03	0.03	0.03	0.04	0.04
Obs	83,620	80,336	77,141	74,051	71,110	68,264	65,481	62,760	73,235	61,293

Table 19: PFT and future mutual fund return gaps

Note: This table reports results from panel regressions that regress future mutual fund return gaps (*ReturnGap*) on PFT and a number of other explanatory variables at quarterly frequency. The dependent variables are k-quarter ahead return gaps as defined by Kacperczyk, Sialm, and Zheng (2008). Standard errors (in parentheses) are double-clustered by fund and quarter. Time fixed effects are added to each regression. *** p<0.01, ** p<0.05, * p<0.1.