Mutual Fund Competition and Profiting from the Post Earnings Announcement Drift

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Abstract

This paper examines how competition affects the performance of mutual funds aggressively pursuing the post earnings announcement drift (PEAD) strategy. We find that competition significantly erodes the performance of these funds. Amid increased competition, there is also increased diversity in the sophistication of implementing the strategy by funds. A group of funds aggressively pursuing the strategy successfully avoid competition and generate superior performance. The identities of these low-competition funds are persistent. Moreover, these funds tend to hold and trade on stocks with high trading costs and high idiosyncratic volatility, presumably to avoid crowding. Our findings suggest that for these low-competition funds, the benefit of avoiding competition outweighs the downside of incurring high trading cost.

1. Introduction

Many hedge funds, mutual funds, and institutional money managers use investment strategies based on accounting anomalies documented in the academic literature. The popularity of anomaly-based quantitative equity strategies is evidenced in a survey by Richardson, Tuna, and Wysocki (2010). A majority of investment professionals responding to the survey indicate that they have and will continue to use such strategies in the future. Moreover, the number of institutional investors and the share of the equity market managed by them have increased substantially in the recent decades.

The popularity of anomaly-based strategies along with the rapid growth of the institutional investment industry also means that competition among these investors has become increasingly relevant for the profitable implementation of quantitative equity strategies. These strategies are largely based on published academic studies and rely on publicly available accounting information as input. As a result, they are, by nature, easy to mimic once the initial hurdles of data and computing power are overcome. As a result, investors following such strategies often end up with very similar positions, and their collective trading can generate a large price impact, quickly eroding profits. Stein (2009) further points out that many anomaly-based strategies, such as drift, momentum, and accruals, are vulnerable to extreme competition, or "crowded trades", because these strategies do not have a "fundamental anchor." Thus competition may be of serious concern for the performance of funds trading on such strategies. For example, Richardson, Tuna, and Wysocki (2010) point out that the increased amount of capital dedicated to these strategies may have accelerated the decay of their profitability.

However, recent studies also suggest a possible confounding effect. Fama and French (2010) characterize the recent growth of mutual funds, which account for the bulk of growth of the investment management industry, as "the entry of hordes of mediocre funds posturing as informed managers." There is also evidence that fund investment decisions are heavily influenced by fund investors' sentiment, or "dumb money" (Frazzini and Lamont 2006). It is unclear in what direction competition driven by unskillful funds or "dumb money" affects the profitability of anomalies-based strategies.

One anomaly that has been closely scrutinized by researchers is the post earnings announcement drift (PEAD). PEAD is perhaps the first widely-documented accounting anomaly (e.g., Ball and Brown 1968; Foster, Olsen, and Shevlin, 1984; and Bernard and Thomas, 1989 and 1990). Furthermore, profitable implementation of PEAD has been the subject of several prior studies (e.g., Bhushan 1994; Ke and Ramalingegowda 2005; Ng, Rusticus, and Verdi 2008; and Richardson, Tuna, and Wysocki 2010).[1] However, these studies so far have only looked at the profitability of hypothetical trading strategies based on estimated trading costs; they do not directly look at the actual performance of institutional investors trading on the strategy. Furthermore, these studies have not examined the competition effect.

In this study, we perform empirical analysis on the competition faced by actively-managed equity mutual funds in their pursuit of the PEAD strategy. We complement the above-mentioned studies by addressing several issues they leave open. More specifically, we document the popularity of this strategy among mutual funds, characterize the competition they face when implementing the strategy, and finally, examine the impact of competition on actual fund performance.

The key concept in our empirical study is the level of competition a fund faces when it trades on PEAD. We develop an empirical measure of competition using the data on mutual

[1] In addition, Khandani and Lo (2011) show that the performance of a PEAD-based strategy suffered greatly during the "quant crisis" of August 2007, suggesting highly correlated positions on the PEAD strategy among institutional investors.

fund portfolio holdings. It is constructed in two steps. We first obtain a competition index for each stock, based on how many funds aggressively pursuing the PEAD strategy hold the stock, scaled by the average number of such aggressive funds holding stocks with similar size, book-to-market ratio, and momentum characteristics. Funds aggressively pursuing PEAD are defined as those ranked in the top decile in terms of their intensity of trading on PEAD. [2] Relative to the entire sample of funds, these aggressive funds are more likely those with an intentional PEAD strategy and potentially generate more direct impact on the profitability of the strategy. At the second stage, we take the average of the stock-level competition index across all stocks held by a fund, weighted by fund portfolio weights, to obtain a fund-level competition index. Thus, a fund faces a high level of competition when it holds stocks that are held by many funds aggressively pursuing the PEAD strategy.

Our analysis includes a large sample of active equity mutual funds during the period from 1990 to 2013. We report several interesting findings. First, mutual funds on average trade on PEAD, and a subset of funds trade on PEAD aggressively and persistently. The persistence suggests the likelihood that these funds pursue the PEAD strategy intentionally, rather than by chance. However, there is at best marginal evidence that funds aggressively pursuing the PEAD strategy deliver abnormal performance.

Second, over time there is a trend of increasing competition among mutual funds trading on PEAD. Meanwhile, there is also a large dispersion in the level of competition faced by different funds, and the identities of both low-competition and high-competition funds are persistent. Thus, the dispersion in the level of competition may not be completely by chance, and

[2] We use the SUE Investment Measure SIM (and its rolling four-quarter average SIM) to quantify the aggressiveness of fund trading on PEAD. SIM is in essence the covariance of fund portfolio weight change with the Standardized Unexpected Earnings (SUE) of stocks in the fund portfolio. A fund has a positive SIM, and therefore pursues the PEAD strategy by our definition, if it buys high SUE stocks and sells low SUE stocks.

to some extent may be due to intentional differences in the ways these funds implement their strategies.

Third, competition has a strong negative impact on fund performance. For example, funds with a low-competition aggressive PEAD strategy (i.e., funds aggressively pursuing the PEAD strategy and facing low competition) significantly outperform funds with a high-competition aggressive PEAD strategy (i.e., funds aggressively pursuing the PEAD strategy and facing high competition) by 2.07% in terms of before-expense returns during the year after fund ranking. Such a performance difference is robust to the control of an extensive set of fund characteristics and fund skill measures documented in existing studies, and by various performance measures we look at. The outperformance of funds with a low-competition aggressive PEAD strategy, and the persistence of their identities, suggest that these funds may have intentionally implemented the PEAD strategy in a way to avoid crowded trades, and are successful in generating superior performance.

Finally, we investigate how the low-competition funds manage to avoid competition when they implement the PEAD strategy. We find that relative to high-competition funds, low-competition funds hold stocks that are more difficult to trade, i.e., those with higher trading cost and higher return volatility. This highlights the double-edged effect of trading cost on the profitable implementation of an anomaly-based strategy. High trading costs reduce the profitability of a strategy; yet, anomalies are typically stronger among stocks with higher trading costs, possibly due to less competition. It appears that the low-competition funds have extra skills in selecting, among the less liquid stocks, the ones with large misevaluation, as evidenced by their outperformance.

Our study is related to a few streams of existing literature. First, Ali, Chen, Yao, and Yu (2008) examine mutual fund trading on the accruals anomaly. They report that funds on average do not trade on the accruals anomaly, but a small subset of funds aggressively pursuing that strategy deliver superior performance, albeit they are subject to the adverse effect of arbitrage risk.[3] Our analysis shows that, trading on PEAD is a popular strategy among mutual funds. Further, in contrast to the performance of funds aggressively pursuing the accruals strategy, funds aggressively trading on PEAD on average do not generate significant abnormal performance. Given the popularity contrast between the two strategies, the performance difference could well be due to the different level of competition for these two strategies.

Second, several studies have noted the intensified competition in the fund industry. So far these studies mainly examine the effect of competition on fund fees (Wahal and Wang 2010; Khorana and Servaes 2004; Coates and Hubbard 2007; and Gil-Bazo and Luis-Verdu 2009). The impact of competition on fund performance remains an open issue. The only exception is Wahal and Wang (2010), who examine the impact of competition from new entry on the performance of incumbent funds. The type of competition examined in our study is different than theirs.

Finally, our paper is related to a body of studies examining whether the PEAD strategy is profitable after trading cost. Ke and Ramalingegowda (2005), using the 13F institutional holdings data, report that transient institutional investors on average trade on PEAD. Further, based on estimated trading costs, they conclude that the aggregate PEAD trades by these institutions are profitable. Battalio and Mendenhall (2011) also report significant profit for a hypothetical strategy taking advantage of timely information on earnings surprises. However, a few other studies, including Bhushan (1994), Chordia, Goyal, Sadka, Sadka, and Shivakumar

[3] In addition, Green et al. (2011) show that possibly due to competition by hedge funds, the paper hedge strategy based on the accrual anomaly (i.e., taking long position in the bottom accrual decile and short position in the top accrual decile of stocks) has been dramatically reduced in recent years.

(2009), Ng, Rusticus, and Verdi (2008), and Richardson, Tuna, and Wysocki (2010), conclude that the hypothetical PEAD trading strategy cannot be profitably implemented net of trading cost. Therefore, whether PEAD can be profitably exploited remains a contended issue. One reason for the different conclusions in the literature is that different trading cost estimation methods are used.[4] The relative advantage of our analysis is that the reported fund net returns are already net of *actual* transaction cost, thus our conclusions are not dependent on trading cost estimation. To reach the conclusion, we also control for fund characteristics known to be associated with fund performance, and fund trading on various other strategies. Our analysis further shows that possibly due to its relation with competition, trading cost has a double-edged effect on the profitability of the PEAD strategy.

The remainder of this paper is organized as follows. Section 2 describes the mutual fund sample, measures of fund trading on the drift anomaly, and measures of competition. Section 3 provides main empirical results - the extent to which funds trade on the drift anomaly, and whether competition affects the performance of funds aggressively trading on PEAD. Section 4 provides further analysis on additional issues. Section 5 concludes.

2. Mutual Fund Sample, SUE Investing Measure, and Competition Index

2.1 Mutual Fund Sample

We combine the CRSP Survivorship Bias Free Mutual Fund Database with the Thomson Financial CDA/Spectrum Database to obtain our mutual fund sample. The CRSP data provide

[4] For example, Ke and Ramalingegowda (2005) use the empirical transaction cost model estimated by Keim and Madhavan (1997), which is based on trades of large institutions during a three-year period (1991 to 1993). Battalio and Mendenhall (2011) examine quoted bid-ask spreads. Chordia et al. (2009) estimate the price impact component of transaction costs based on the TAQ data. Ng et al. (2008) measure trading costs in the form of quoted spreads, effective spreads, as well as an indirect cost measure developed by Lesmond, Ogden, and Trzcinka (1999) based on the frequency of zero return days. Finally, Richardson et al. (2010) uses a transaction cost model similar to Korajczk and Sadka (2004), estimated using a proprietary trading cost dataset from a large institutional investor.

information on monthly fund net returns and total net assets, as well as annual fund characteristics such as expense ratio and turnover. The Thomson data provide information on fund stock holdings at quarterly or semiannual frequency.

From the Thomson data, we select all funds with reported investment objective of aggressive growth, growth, and growth and income. These three categories of funds represent the majority of actively managed US domestic equity funds. Passive index funds and funds with apparently misreported investment objectives are further removed from the sample. Multiple share classes of a fund in the CRSP data are combined into a single fund before matching with the Thomson data. To ensure data accuracy, we exclude fund-quarter observations if the total net assets are below one million dollars or the total market value of reported holdings is less than 50 percent or more than 150 percent of the total net assets. To ensure reliable measures of fund trades, we also require that the current date of fund holdings is no more than six months apart from its previous date of fund holdings.

The Thomson dataset goes back to 1980. However, in the early sample period, the number of funds in the cross-section is small and does not permit a meaningful analysis involving double-sorting on fund trading on PEAD and fund competition. We therefore choose the sample period from 1990 to 2012 for analysis -- with the last year of fund holdings data being 2012 and the last year of fund return data being 2013 since we examine fund performance during the year after fund ranking.

During this period, we have 2,319 unique U.S. active equity funds in the sample. In Table 1, we report characteristics of the sample funds over the entire sample period as well as snapshots taken in a few representative years: 1990, 1995, 2000, 2005, and 2012. Among the 2,319 funds, 232 are aggressive growth funds; 1,757 are growth funds; and 330 are growth and income funds. On average, the total net assets of sample funds is $730.29 million, with an annual return of 9.59 percent, an annual turnover ratio of 96.12 percent, and an annual expense ratio of 1.18 percent. The average fund age (years elapsed since the fund organization date), is 9.64 years. The mean number of stocks held in a fund is 113, and the median is 67. The number of funds increases from 522 in 1990 to 1,156 in 2012.

Mutual funds report their portfolio holdings either quarterly or semiannually. On average, 28.36 percent of sample funds report holdings semi-annually. This proportion is high in the early period (63.25 percent in 1995), and is low again in recent years (4.29 percent in 2012).[5]

2.2 Standardized Unexpected Earnings and Post Earnings Announcement Drift

Following Bernard and Thomas (1990), we compute standardized unexpected earnings (SUE) as:

$$SUE_{j,t} = \frac{E_{j,t} - E_{j,t-4} - c_{j,t}}{\sigma_{j,t}} \tag{1}$$

where $E_{j,t}$ is the quarterly earnings (COMPUSTAT quarterly data item ibq) reported during quarter t, $E_{j,t-4}$ is earnings reported four quarters ago. $c_{j,t}$ and $\sigma_{j,t}$ are the time series mean and standard deviation, respectively, of ($E_{j,t} - E_{j,t-4}$) over the preceding 8 quarters, with a minimum of 4 quarters required for the calculation to be valid. Earnings announcement dates are from the COMPUSTAT quarterly file. For missing announcement dates, we assume that earnings are

[5] The SEC-mandated frequency for mutual fund portfolio disclosure is quarterly before 1984, semiannually afterwards, and switched back to quarterly after May 2004. Many funds voluntarily report holdings quarterly during the period when the mandatory disclosure frequency was semiannual.

reported two months after fiscal quarter-end.[6] However, when we exclude observations with missing announcement dates we obtain similar results.

Table 2 shows that the PEAD anomaly exists during the sample period from 1990 to 2012. At the end of each calendar quarter Q0, we identify all publicly traded stocks with valid SUE observations but exclude stocks with quarter-end price below $1 (to avoid market microstructure issues in measuring returns). There are 412,245 stock-quarter observations in the sample. For convenience, we refer to this sample as the "Stock Universe". Within the Stock Universe, we sort stocks to form equal-weighted decile portfolios based on SUE. We calculate returns to the equal-weighted decile portfolios during each of the four subsequent calendar quarters (Q1 to Q4) after Q0. The portfolios are rebalanced at the beginning of each quarter. If a stock is delisted during a quarter, we assume that its return during the remaining period of the holding quarter is the delisting return reported in CRSP. If the CRSP delisting return is missing, we follow Shumway (1997) to assume that the delisting return is -30% if delisting is performance related, and zero otherwise.

In the “Stock Universe,” there are on average 414 stocks in each decile. In the calendar quarter immediately after portfolio formation (Q1), the return spread between P10 and P1 portfolios is 3.48% ($t = 7.15$). The spread remains significantly positive for Q2 (2.25%) and Q3 (1.59%), and becomes insignificantly negative during Q4 (-0.70%). The pattern of declining returns of the PEAD strategy from Q1 to Q3 and the negative returns during Q4 is consistent with the findings of prior studies, e.g., Bernard and Thomas (1990). Thus, in order to take advantage of the drift anomaly, investors have to trade frequently. We further compute the Fama-

[6] From 1970 to 2002, the SEC-mandatory deadline for financial reporting is 45 days after fiscal quarter-end and 90 days after fiscal year-end. Starting from 2002, and with a three-year phase-in period, the mandatory reporting deadline is accelerated to 35 days after fiscal quarter-end and 60 days after fiscal year-end.

French (1993) three-factor and Carhart (1997) four-factor alphas for the quarterly return spread between P10 and P1 portfolios and obtain consistent results.

We perform similar analysis among stocks that are held by mutual funds. In each quarter we identify all stocks from the "Stock Universe" that are held by at least one fund in our sample during that quarter. From 1990 to 2012, there are altogether 291,269 stock-quarter observations in this sample (referred to as "Stocks Held by Funds"). Within this sample, we assign stocks into equal-weighted decile portfolios based on the SUE decile breakpoints of the "Stock Universe." Rather coincidentally, as it is shown in the table, the average number of stocks in each decile is quite evenly distributed, between 306 and 311. The return spreads between P10 and P1 deciles, from Q1 to Q4, are 3.07%, 2.01%, 1.34%, and -0.50%, respectively. That is, the drift is only slightly weaker within this sample than that obtained for the "Stock Universe." The three-factor alphas and four-factor alphas exhibit a similar pattern.

Figure 1 displays the time series variation in the magnitude of the PEAD anomaly, which is measured by the top-bottom SUE stock decile return difference. The return spread is first computed for the first quarter Q1 after the portfolio formation, and then summed over for a given year. This return spread is highest in 1999 and lowest in 2009. It is relatively high during the 1990s, but exhibits a slight drop in the 2000s, which is consistent with that reported by a few other studies, e.g., Richardson, Tuna, and Wysocki (2010).

2.3 SUE Investing Measure

We use the SUE investing measure (SIM) to quantify how actively a fund takes advantage of the post earnings announcement drift. This measure is in the spirit of the momentum investing measure of Grinblatt, Titman, and Wermers (1995). A fund's SUE investing measure is the sum of the products of active changes in fund portfolio weights and SUEs (cross-sectionally standardized) of individual stocks held by the fund:

$$\hat{SIM}_{i,t} = \sum_{j=1}^{N_{i,t}} (w_{i,j,t} - \tilde{w}_{i,j,t-k}) \frac{SUE_{j,t} - \mu_t(SUE)}{\sigma_t(SUE)} \qquad \text{(k=1 or 2)} \qquad (2)$$

where $SUE_{j,t}$ is standardized expected earnings of firm j, with current earnings reported between fund i's prior and current portfolio reporting date (which is in quarter t). $\mu_t(SUE)$ and $\sigma_t(SUE)$ are the cross-sectional mean and standard deviation of $SUE_{j,t}$, over all stocks in the Stock Universe during the calendar quarter of earnings announcements. $N_{i,t}$ is the total number of unique stocks held by fund i in quarter t and t-k (k=1 for funds reporting holdings quarterly and k=2 for funds reporting holdings semi-annually).

Further, $w_{i,j,t}$ is fund i's portfolio weight on stock j at the end of quarter t. Since our interest is on fund stock selection decisions, we focus on the equity portion of the portfolio, and define $w_{i,j,t}$ as the value of stock j held by the fund divided by the total value of stocks held by the fund at quarter end (instead of the total net assets of the fund). When calculating $w_{i,j,t}$, we only include stocks in the "Stock Universe" (with valid SUE observations and a minimum price of $1 at the end of quarter t). When calculating active changes of portfolio weights, we follow Kacperczyk, Sialm, and Zheng (2005) to control for the effect of passive weight changes due to stock price changes. Specifically, we compute $\tilde{w}_{i,j,t-k}$ as the portfolio weight measured at quarter t under the assumption that the fund holds its positions, without trading, from its previous reporting date t-k. Let $R_{j,t-k,t}$ denote the return for stock *j* from quarter t-k to t, then,

$$\tilde{w}_{j,t-k} = \frac{w_{j,t-k}(1+R_{j,t-k,t})}{\sum_{j=1}^{N} w_{j,t-k}(1+R_{j,t-k,t})} \quad \text{(k=1 or 2)} \qquad (3)$$

By construction, $SUE_{j,t}$ becomes public information at a time between the two portfolio reporting dates t-k and t. Also, note that the cross-sectionally standardized $SUE_{j,t}$ has zero mean in the "Stock Universe.", and that portfolio adjustment, $w_{i,j,t} - \tilde{w}_{i,j,t-k}$, should be summed to zero for each fund. Therefore, $\widehat{SIM}$ can be broadly viewed as the covariance between active portfolio weight changes and standardized SUEs. As a result, a portfolio of randomly selected stocks from the "Stock Universe" has an expected $\widehat{SIM}$ of zero. A high $\widehat{SIM}$ indicates that a fund trades to increase holdings of high-SUE stocks and decrease holdings of low-SUE stocks.

It is possible that a fund may have a high $\widehat{SIM}$ because of luck instead of deliberate trading. However, a fund deliberately trading on the drift anomaly is more likely to have persistently high $\widehat{SIM}$s over multiple quarters. To increase the likelihood that our measure captures intentional trading instead of luck, we compute the rolling average of $\widehat{SIM}$s over four quarters (from quarter t-3 to t), and denote it SIM:

$$SIM_{i,t} = \sum_{k=0}^{3} S\hat{I}M_{i,t-k} \tag{4}$$

For funds reporting their holding semi-annually, since there are only two reported snapshots of fund holdings during quarters t-3 to t, SIM is the average of the two $\widehat{SIM}$s that are measured semiannually.

2.4 Fund Competition Index

We quantify the fund-level competition based on the competition a fund faces from funds aggressively trading on PEAD.[7] The competition measure is constructed in two steps.

[7] Competition a fund faces could be multifaceted. We consider an alternative competition measure that captures the general competition a fund faces from all other funds, instead of D10 SIM funds. Our finding shows that the PEAD-specific competition measure outperforms the general competition measure in terms of identifying successful funds.

The first step is to construct a competition index at the stock level. For each stock j in quarter t, we count the number of all funds ranked in the top SIM decile holding stock j (n_{jt}) and the average number of top SIM-decile funds holding stocks in the same size, BM, and momentum benchmark portfolio as stock j (n^*_t). The benchmark portfolios are constructed in each quarter, following the procedure of Daniel, Grinblatt, Titman, and Wermers (DGTW; 1997). The stock level competition measure is the characteristics-adjusted number of funds holding the stock, n_{jt} / n^*_t.

The second step is to aggregate the stock-level competition index to the fund level using the portfolio weight change of each stock in a fund's portfolio. As a result, the competition index measure for a fund is defined as:

$$C\hat{I}M_{i,t} = \sum_{j=1}^{N_{it}} w_{i,j,t}(n_{jt} - n_t^*) \tag{5}$$

where n_{jt} and n^*_{jt} are the numbers of the top SIM4 decile funds holding stock j and stocks with similar characteristics as stock j. $w_{i,j,t}$ is portfolio weight of stock j in fund i in quarter t, and $N_{i,t}$ is the total number of unique stocks held by fund i in quarter t.

Finally, similar to SIM, we compute the rolling average of competition index measures over four quarters (from quarter t-3 to t), and denote it CIM:

$$CIM_{i,t} = \frac{1}{4}\sum_{k=0}^{3} C\hat{I}M_{i,t-k} \tag{6}$$

Wahal and Wang (2010) measure competition between incumbent funds and entrant funds based on their portfolio overlaps. Our measures are similar to theirs but with some differences. Their measure is based on the dollar amount of fund holdings, and a large incumbent facing small entrants is naturally defined as having low competition. While this feature is justifiable in the problem they analyze, it may confound the effects of competition and fund size on performance in our application. Our measures essentially replace the ratio of the dollar amount of fund holdings in their expression by the number of funds holding a stock (adjusting for stock characteristics), and thus removing the influence of fund size.

3. Empirical Results

3.1 Characterizing Mutual Fund Trading on PEAD

3.1.1 SIM: Averages and Time Series Variations

Panel A of Table 3 shows that mutual funds, as a whole, trade on the drift anomaly. For each quarter, we compute cross-sectional distribution statistics of SIM for sample funds and report the time-series averages of the statistics. The time-series t-statistics are computed following the Newey-West procedure with a lag of 4 quarters. The mean of SIM is 1.29% (t =5.74) and the median is 0.97% (t = 4.32).

In untabulated analysis, we further show that the patterns are not driven by factors such as fund trading on price momentum and fund preference for large stocks and growth stocks. Specifically, we calculate characteristics-adjusted SUE, which is the estimated residual from cross-sectionally regressing SUE on the logarithm of market cap, the book-to-market ratio, and stock returns during past 12 months, as well as SUEs during the previous three quarters. We replace SUE in Equation (2) by the estimated characteristics-adjusted SUEs from the above regression to construct the characteristics-adjusted SIM. We find that the means and medians of characteristics-adjusted SIM and characteristics-adjusted SIM are significantly positive, similar to the patterns reported in Table 3 for unadjusted measures.

Panel A of Figure 2 displays the time series variations in the intensity of fund trading on PEAD. Interesting, it shows that the average PEAD trading intensity (measured by SIM4) across all funds is higher in early sample years and exhibits a declining trend. Panel B of Figure 2 further shows that average trading intensity across the top-decile SIM funds also decline during the sample period. However, since the cross-section of the funds expanded dramatically, the result means that there are more funds trading on PEAD at this high intensity in recent years.

3.1.2 Persistence of SUE Investing Measures

We further investigate whether high SIM funds trade on PEAD deliberately by looking at SIM persistence. If some funds pursue the PEAD strategy intentionally, their SIM would persist over time. Panel B of Table 3 reports the persistence of SIM. In each quarter Q0, we sort funds into deciles based on SIM. D10 funds are the top 10% funds with the highest SIM, and D1 funds are those with the lowest SIM. For comparison purpose, we also identify a group of INACTIVE funds, who are the 10% of funds with SIM closest to, and centered around, zero. We trace the average $\widehat{SIM}$s of each fund decile in the subsequent four quarters, Q1 to Q4.[8] The average $\widehat{SIM}$s of D10 funds for Q1 to Q4 are 4.05%, 3.40%, 3.51%, and 3.88%, respectively, all of which are significantly positive. $\widehat{SIM}$s of D10 funds are also significantly higher than those of INACTIVE funds in Q1 to Q4.[9] In untabulaed analysis, we find that the persistence of SIM lasts for as long as five years after initial fund ranking.

3.2 Performance Analysis

[8] Some funds in our sample report portfolio holdings semiannually. The results for Q1 and Q3 are based only on funds reporting portfolio holdings quarterly, whereas the results for Q2 and Q4 are based on both funds reporting quarterly and funds reporting semiannually. For robustness, we repeat our analysis after excluding semiannually-reporting funds, and obtain similar results.

[9] D1 funds also exhibit some persistence in having low SIMs in future quarters. We find that this is related to fund investment style. When we perform cross-sectional regression of SIMs in subsequent quarters onto decile dummies for SIM of Q0 as well as measures of fund styles, i.e., fund trading on size, book-to-market, and momentum, the coefficients for dummies for low SIM deciles are no longer significantly negative. On the other hand, the coefficients for dummies for high SIM deciles remain significantly positive.

3.2.1 Fund Performance Measures

We employ an extensive set of performance measures. Since the purpose of this study is to evaluate the stock selection ability of funds, fund returns and fund performance measures derived from fund returns, are net of fund trading cost but before fund expense ratio (i.e., the percentage fund management fees charged to fund investors).

First, at the end of each quarter Q0, we calculate the before-expense fund return for quarter Q1 and for year Y1 (the four quarters after Q0) for each fund. To obtain the before-expense quarterly fund return, we start from the after-expense monthly fund net returns reported in the CRSP data, compound them into quarterly returns, and then add 1/4 of the annual fund expense ratio. Annual before-expense returns are computed similarly. We then compute the average before-expense returns for Q1 and Y1 for each fund decile sorted on SIM, and for each CIM tercile within the D10 funds. This results in quarterly time-series observations of Q1 and Y1 returns for each fund group.

In addition, we consider the Fama-French (1993) three-factor alpha and the Carhart (1997) four-factor alpha. They are based on the following models respectively:

$$R_t - R_{ft} = \alpha + \beta_1 RMRF_t + \beta_2 SMB_t + \beta_3 HML_t + \varepsilon_t \tag{7}$$

$$R_t - R_{ft} = \alpha + \beta_1 RMRF_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 UMD_t + \varepsilon_t \tag{8}$$

where R_t is the fund decile return of quarter Q1 or of year Y1. R_{ft} is the risk-free rate as proxied by the yield on Treasury bills with one-month maturity. $RMRF_t$ is the market return (CRSP value-weighted index return) in excess of risk free rate; SMB_t, HML_t, and UMD_t are size, book-to-market, and momentum factors, obtained from Ken French's website.[10] Depending on

[10] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

whether fund decile return is measured for Q1 or Y1, monthly observations of R_{ft}, RMRF, SMB, HML, and UMD are compounded into corresponding quarterly or annual observations.

The factor-based performance measures have a few known issues. First, the factors are measured before trading cost, while fund returns, the dependent variable, is measured after trading cost. This specification is likely to bias the estimated alpha downwards when trading cost is a significant concern. This problem may be especially severe for funds trading on price momentum or signals correlated with price momentum (i.e., PEAD). For example, using mutual fund data, Edelen, Evans, and Kadlec (2011) report evidence that trading cost largely offsets the benefit of momentum trading. Second, a recent study by Cremers, Petajisto, and Zitzewitz (2013) reports that passive portfolios such as the S&P index has significantly non-zero alphas under the factor based models, suggesting potential problems with the factor construction. Finally, prior studies such as Daniel et al. (1997) and Kothari and Warner (2001) have also shown that more powerful performance measures, as compared to the factor-based performance measures discussed above, can be obtained by incorporating information about the characteristics of fund portfolio holdings or trades.

To incorporate fund holdings information into performance evaluation while accounting for trading cost, we adopt a fund style-based benchmark approach. We measure the style-adjusted performance of a fund as the fund net return in excess of the average net return of funds with similar portfolio styles. Specifically, we consider the following two measures: size and book to market (SIZE-BM) style-adjusted fund return, and size, book to market, and momentum (SIZE-BM-MOM) style-adjusted fund return. At the end of the fund ranking quarter Q0, we use sequential sort to classify funds into different benchmark groups based on their investment styles along the dimensions of size, book-to-market ratio, and momentum. We then compute the average fund returns for each benchmark group for Q1 and Y1. For any given fund, its style-adjusted return is the fund return in excess of the return of its corresponding benchmark group.

We measure fund styles by SIZESCORE, BMSCORE, and MOMSCORE. They are constructed in a way similar to SIM described in Equation (2), but replacing SUE with log market cap, book-to-market ratio, and stock returns during the past 6 months, respectively, and taking the four-quarter rolling averages of the resulting measures.[11] For SIZE-BM benchmarks, we use a sequential 5x5 sort on SIZESCORE4 and then on BMSCORE4. Given that the fund sample size is relatively small in the earlier sample years, for SIZE-BM-MOM benchmarks, we vary the number of benchmark groups to ensure sufficient funds in each group. From 1990 to 1995, we sort funds into 64 benchmark fund groups (4x4x4). From 1996 onwards, we form 125 benchmark fund groups (5x5x5).

3.2.2 Fund Performance across SIM Sorted Portfolios

In Table 4, we report performance across SIM-sorted fund deciles. The results show that D10 funds have mixed performance records depending on performance measures. D10 funds have significantly positive 3-factor alphas for Q1 (the first calendar quarter after portfolio formation) and Y1 (the first calendar year after portfolio formation). However, their 4-factor alphas, SIZE-BM, and SIZE-BM-MOM adjusted returns are not significant. Further, the performance of D10 funds over INACTIVE funds is not impressive. While the performance difference is positive, it is not statistically significant by any measure. For example, based on fund net return, in Q1 (Y1), D10 funds outperform INACTIVE funds by 0.49% (1.10%), with a

[11] When computing the 4-quarter rolling-average style measures, an issue we encounter is that some funds only report holdings semiannually. In order to avoid unnecessarily reducing the number of funds used to compute benchmark returns, we require a fund to have stock holding observations for at least two out of four rolling quarters from Q(-3) to Q0.

t-statistic of 1.41 (1.38). The difference in the four-factor alphas is 0.39% (t = 1.59) for Q1 and 1.50% (t = 1.30) for Y1. Our overall assessment is that funds aggressively pursuing the PEAD strategy do not convincingly generate superior returns.

3.3 Fund Competition Index and Performance across CMs

3.3.1 *Fund Competition Index*

Panel A of Table 5 describes the average magnitude of the competition funds face. The observed average of fund competition measure is significantly positive. The mean and median CIM are 2.37 and 2.13. The Newey-West adjusted t-statistics for these measures are all exceeding 4. Moreover, the cross-sectional standard deviations of these measures suggest that there is also substantial variation in the competition individual funds face.

In Panel C and D of Figure 2, we plot the time series variations of competition for all funds and top SIM-decile funds, respectively. Panel C shows that the average competition faced by these funds is low most of the 1990s, but it visibly takes off in the late 1990s. Since the average intensity of trading on PEAD by these top SIM4 decile funds does not vary dramatically (Panel B of Figure 2), the intensified competition must be due to the increased number of funds. Interestingly, this pattern is similar to that documented by Wahal and Wang (2010) on competition faced by incumbent funds from new entries, which also takes off in late 1990s.

3.3.2 Persistence of Competition

Panel B of Table 5 shows the result on the persistence of fund competition indices. Since our interest is in funds aggressively pursuing the PEAD strategy, we focus on the persistence of CIM among top SIM-decile (D10) funds. In each quarter D10 funds are classified into terciles, T1 (low-competition), T2, and T3 (high-competition) funds in ascending order of CIM. Since the competition level likely varies with the intensity of PEAD trading, we jointly examine their future intensity of PEAD trading and intensity of competition. Specifically, for each CIM tercile ranked in Q0, we report i) the competition index given the future SIM decile, and ii) the faction of funds that are ranked into various SIM deciles in the four subsequent quarters (Q1 to Q4). The table shows that given their future SIM decile ranking, T1 funds continue to have low $\widehat{CIM}$, and T3 continue to have high $\widehat{CIM}$s in subsequent quarters, suggesting these funds persistently engage in (or avoid) competition.

3.3.3 Fund Performance across Competition Terciles

In Table 6, we report performance of D10 funds that are further classified into tercile groups by CIM. The results show that competition makes a difference in fund performance. For Q1, the low-competition funds (T1) generate an average net return of 3.31%, with a three-factor alpha of 0.83%, a four-factor alpha of 0.67%, a SIZE-BM style adjusted return of 0.51%, and a SIZE-BM-MOM style-adjusted return of 0.57%, all significantly positive. By contrast, the high-competition funds (T3) for Q1 generate a three-factor alpha of 0.31%, a four-factor alpha of 0.14%, a SIZE-BM style adjusted return of -0.15%, and a SIZE-BM-MOM style-adjusted return of -0.06%, all insignificantly different from zero. The pattern is similar when performance is measured for the subsequent year, Y1. Further, the performance difference between T1 and T3 is significant. For Q1, T1 outperform T3 in net return by 0.52% (t = 2.25), in the four-factor alpha by 0.53% (t = 1.86), and in the size-BM-momentum style-adjusted return by 0.63% (t = 2.37), suggesting the outperformance of T1 funds is robust after controlling for factor exposure and characteristics adjustment. Moreover, for Y1, T1 outperform T3 in net return by 2.07% (t = 1.92), in the four-factor alpha by 1.15% (t = 1.86), and in the size-BM-momentum style-adjusted return by 2.11% (t = 2.59).

4. Further Analysis

4.1 Regression Analysis: Controlling for Fund Skill Characteristics

Although we have shown that low-competition D10 funds have superior performance, it is possible that these funds may also possess skills other than profiting from PEAD, and therefore its outperformance may not be fully attributable to skillful trading on PEAD. In this section, we consider a broad set of fund characteristics that are shown in the literature to be indicative of fund managers' skills, and examine the performance of low-competition D10 funds by controlling for these fund skill characteristics.

The fund skill characteristics are motivated by the following literature. First, Wermers (2000) finds that the annual fund turnover is positively related to subsequent fund performance. Second, Carhart (1997) shows that fund expense ratio is inversely related to future fund performance. Third, Kacperczyk, Sialm, and Zheng (2005) find that the industry concentration of fund portfolio signals fund ability and is positively correlated with future fund performance. Fourth, Kacperczyk, Sialm, and Zheng (2008) show that unobserved actions of mutual funds, measured by the gap between before-expense fund net return and hypothetical buy-and-hold return based on beginning-of-period holdings, predict fund performance. They suggest that the gap reflects the joint effects of fund manager skills and trading costs. Fifth, Cohen, Coval, and Pastor (2005) show that skilled fund managers tend to make similar stock-picking decisions, and provide a predictive fund performance measure based on the similarity of portfolio holdings. Sixth, Baker, et al. (2010) use the relation between fund trading and stock returns around subsequent earnings announcements to measure fund managers' stock selection ability. Finally, Kacperczyk and Seru (2007) find that the R-square obtained from regressing fund portfolio holdings on changes in analyst stock recommendations is inversely correlated with future fund performance. They argue that relying on public information to pick stocks is a negative signal of manager skills.

The seven fund skill measures of the above studies are referred to as TURN, FEE, ICI, GAP, SIMILAR, EAR, and RPI, respectively. TURN is fund turnover ratio during the past 12 months and FEE is the annual fund expense ratio plus amortized load (one seventh of total load; see Sirri and Tufano, 1998). Details on the other 5 fund skill characteristics, ICI, GAP, SIMILAR, EAR, and RPI, are provided in the Appendix.

To examine the incremental effect of trading on the drift anomaly on performance of low-competition D10 funds, we perform multivariate Fama-MacBeth regressions. The dependent variables are before-expense fund net returns during Q1 and during Y1. The main explanatory variables are the three dummy variables T1, T2, and T3, representing low, medium, and high terciles of D10 funds sorted on the competition index CIM. We also include a variable PSIM, which equals SIM of Q0 if SIM is positive, and zero otherwise. PSIM indicates the level at which funds are trading on the drift anomaly. A positive coefficient on it would indicate that funds trading on the drift anomaly more intensely exhibit better performance. In addition, NSIM equals SIM of Q0 if SIM is not positive, and zero otherwise. Since a negative SIM indicates that the funds do not trade in the direction of the drift anomaly, we do not have any prediction on the coefficient on NSIM. The control variables include the seven fund skill characteristics described above, as well as the following: fund style measures SIZESCORE, BMSCORE, and MOMSCORE, and fund characteristics TNA, FAMTNA, AGE, FLOW, and STDEV. TNA is the logarithm of fund total net assets (TNA). FAMTNA is the logarithm of fund family TNA. AGE is the fund age, defined as the number of years since fund organization date. FLOW is the annual fund flow.[12] These four variables are all measured at the end of Q0. STDEV is the standard deviation of fund net returns over the 12 months prior to the end of Q0. We estimate the cross-sectional regression for each quarter and compute the time series means of the estimated coefficients. To control for serial correlations caused by using overlapping fund return (for Y1) as the dependent variable, we use the Newey-West adjustment with a 4-quarter lag when computing time-series t-statistics.

Table 7 reports the regression results.[13] The coefficients for PSIM are insignificantly positive, suggesting that trading on PEAD does not deliver significant performance. However, the coefficients on the T1 are significantly positive: 0.68 (t = 3.23) for Q1 and 2.39 (t = 3.45) for Y1. In comparison, the coefficients on T2 and T3 are insignificant. Thus, low-competition D10 funds continue to generate significant outperformance after controlling the extensive set of fund skill characteristics already documented in existing studies.

4.2 Fund Trading on Other Market Anomalies

Another potentially confounding issue is that funds may use other anomaly-based trading strategies in addition to trading on PEAD. In this part, we explicitly analyze the effect of fund trading on other market anomalies when evaluating T1 fund performance. For brevity the results described in this section are not tabulated.

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12 Following Sirri and Tufano (1998), we measure mutual fund flow (FLOW) as: $FLOW_{it} = \frac{TNA_{it} - TNA_{it-1}(1+R_{it})}{TNA_{it-1}}$, where TNA_{it} is the total net assets of fund i at the end of quarter t, and R_{it} is the fund return during quarter t.

13 Analyst recommendation data are available after January 1993. Therefore in Table 6, the cross-sectional regressions are performed without including RPI as an explanatory variable for the period before 1993.

First, at stock level, SUE is positively correlated with price momentum (Chan, Jegadeesh, and Lakonishok, 1996). It is likely that funds trading on SUE also trade on price momentum. However, as reported in Table 7, after controlling for fund trading on momentum via the variable MOMSCORE4, T1 dummy remains significantly positive. Thus, trading on price momentum does not explain the profitability of T1 funds.

Another momentum-type anomaly is analyst forecast revision (Chan, Jegadeesh and Lakonishok, 1996). We measure forecast revision as analyst median EPS forecast for the next fiscal year (Y1) during the last month of Q0, in excess of the median EPS forecast for the same fiscal year three months ago, divided by stock price in the last month of Q0. We construct a measure of fund trading on analyst forecast revision, REVIM, and the four-quarter rolling average REVIM4, in a way similar to SIM. We find that the correlation between SIM and REVIM4, while positive, is not significant. Further, after including REVIM4 as an additional control variable in Table 7, the coefficient for T1 remains significant.

Finally, we construct measures of fund trading on an extended list of value and earnings quality anomalies. Specifically, we include value indicators earnings-to-price ratio and sales growth (Lakonishok, Shleifer, and Vishny, 1994), the earnings quality measure accruals (Sloan 1996), investing and financing activity measures capital expenditure (Titman, Wei, and Xie, 2004), net share issuance (Pontiff and Woodgate, 2008), external financing (Bradshaw, Richardson, and Sloan, 2006), and total asset growth (Cooper, Gulen, and Schill, 2008).

We find that funds aggressively trading on PEAD (i.e., D10 funds and T1 funds) generally trade in the opposite direction suggested by these additional strategies. For example, both D10 funds and T1 funds tend to buy high accruals stocks and sell low accruals stocks. Not surprisingly, controlling for fund trading on these additional anomalies does not explain away the performance of T1 funds.

4.3 How Do Funds Avoid Competition? The Role of Trading Cost

In theoretical models of competition among sophisticated investors (e.g., Stein 2009), which stock has crowded trade is unpredictable. Our finding on the persistence of low-competition D10 funds reveals an intriguing possibility that some funds can actually predict the competition level across stocks and successfully execute their trading strategy to avoid crowded trades. In this section we examine what information T1 funds rely on in their success to stay away from competition. We conjecture that certain ex ante stock characteristics may be related to the likelihood of competition or crowding. In particular, funds are more likely to compete on stocks that are liquid and thus easy to trade. To avoid crowded trades, then, low-competition funds may end up selectively investing in stocks that are illiquid and difficult to trade.

We examine this conjecture empirically, by comparing the liquidity profile of stocks held and traded by funds across competition terciles. The liquidity characteristics we consider are an all-inclusive set of variables that have been used in the empirical trading cost models of Bhushan (1997), Keim and Madhavan (1997), Lesmond et al. (1999), and Korajczyk and Sadka (2004).[14] The variables include the following. STDR is the average annualized standard deviation of daily stock returns in Q0 of stocks held by the fund. IDIORISK is the average annualized standard deviation of the residuals in the regression of daily stock returns on the three Fama-French factors, measured during quarter Q0. STKTURN is the quarterly cross-sectional percentile rank of daily turnover, ranked for NYSE/AMEX and NASDAQ separately. ILLIQ is the quarterly

[14] We use the stock characteristics of these trading cost models but do not directly estimate trading costs based on the models, because trading cost estimation requires additional information on trade size. Trade order splitting has become a common practice and it is unclear how mutual funds in our sample split their trades.

cross-sectional percentile rank of the illiquidity measure defined in Amihud (2002), ranked for NYSE/AMEX and NASDAQ separately. 1/P is the inverse of stock price at the beginning of a quarter. DY (%) is a stock's dividend yield. R2 is the R-square of regressing monthly returns of past 36 months onto the NYSE index. P-RATIO is the stock price at the beginning of the period divided by the price six months ago, minus one. S&P represents a stock having a S&P500 membership. NASDAQ is a dummy variable for Nasdaq stocks. SIZE is the average market cap (in $thousands) at the beginning and end of the period. ZERO is a dummy for zero daily return for a stock. %S&P, %NASDAQ, and %ZERO are the fraction of stocks having S&P500 membership, being listed in NASDAQ, and having zero daily stock returns, respectively. For each liquidity characteristic, we first calculate the weighted average for each fund, where the weights are the portfolio weights. We then average the fund-level measure within each fund group (SIM deciles, and CI terciles among D10 funds). The results reported in Table 8 reveal a striking contrast between T1 and T3 funds: T3 funds hold stocks that are substantially more liquid than stocks held by T1 funds. This is consistent with our conjecture.

Given the substantial difference in liquidity characteristics, one may wonder whether T1 funds outperform because they hold illiquid stocks, since, after all, illiquid stocks tend to generate high returns in the form of a liquidity premium (e.g., Amihud 2002). We perform multivariate Fama-MacBeth regressions to test this possibility. The regressions are similar to those performed in Table 6, except that we replace fund skill measures with fund liquidity characteristics. The dependent variables remain fund returns in Q1 and Y1. The main explanatory variables remain PSIM, NSIM, T1, T2, and T3. Due to high correlations among some of the liquidity characteristics, we only include a subset of these variables: IDIORISK, STKTURN, ILLIQ, and %ZERO. We keep control variables SIZESCORE, BMSCORE,

MOMSCORE, FEE, FUNDTURN, TNA, FAMTNA, AGE, FLOW, and STDEV. The results suggest that liquidity characteristics do have some impact on fund performance. However, the outperformance of T1 funds is not explained by liquidity characteristics. The results are not reported for brevity.

In untabulated analysis, we further include a liquidity factor in the factor-based model to examine fund performance. Specifically, we compute the five-factor alpha of T1 and T3 funds, where the five factors are the Carhart four factors plus the liquidity factor (using either the Sadka (2006) liquidity factor or the Pastor and Stambaugh (2003) liquidity factor, both available from WRDS). The alpha difference between T1 and T3 funds remains significant under these liquidity-augmented factor models. In fact, the mean returns on both liquidity factors are insignificantly negative during our sample period, suggesting that funds are unlikely to earn a premium merely because of their positive loading on the liquidity factors during this period.

The observation that low-competition funds thrive on highly illiquid stocks may appear intriguing. It in fact highlights the due roles of trading cost in the profitable implementation of a trading strategy. A direct effect of trading cost is to reduce the net profit of any strategy. However, there is a more subtle, indirect, effect. Due to lack of competition, anomalies tend to be stronger among less liquid stocks. In the traditional, equilibrium view of the market, trading cost serves as an upper bound to mispricing, to the extent that after trading cost the anomaly-based trading is not profitable. However, the stock market may not always be in such equilibrium and it is possible that for some individual stocks, mispricing turns out to exceed the trading cost bound. Such temporary disequilibrium may happen more often to stocks with higher trading cost; in other words, price deviation from fundamental value may exceed the trading cost bound more frequently and more dramatically among less liquid stocks. This creates profitable opportunities for low-competition funds. Of course, this also means that low-competition funds are not merely implementing a mechanical PEAD strategy that buys all illiquid high-SUE stocks without discrimination. They likely possess extra skills in judging the magnitude of misevaluation on individual stocks and in executing trades, as reflected in their profitable implementation of the PEAD strategy.

5. Conclusion

This study provides the first empirical analysis on the effect of competition on the performance of mutual funds aggressively pursuing anomaly-based trading strategies. We have three main findings. First, we provide evidence that the post earnings announcement drift is a popular investment strategy among actively managed US equity mutual funds. However, perhaps due to intense competition, funds aggressively trading on PEAD on average do not generate substantial outperformance. Second, we show that competition matters for cross-sectional fund performance. Among funds aggressively trading on PEAD, performance is negatively correlated with a strategy-specific measure of fund competition. We also find that a subset of funds (namely, the low-competition D10 funds) manage to aggressively trade on PEAD, avoid crowded trades, and generate superior performance. Their identities are persistent. Therefore, amid increased competition, investment sophistication has evolved and strategies of some funds have adapted. This is consistent with the adaptive evolution view of the financial market. Finally, we report evidence that low-competition funds manage to avoid competition by investing in high trading cost stocks. This suggests that competition and trading cost, while correlated, have distinct effects on the performance of anomaly-based investment strategies; when implementing a strategy, avoiding competition may be an important factor to consider in addition to optimizing on trading cost.

Appendix: Fund Skill Characteristics

A.1. ICI

The industry concentration index follows Kacperczyk, Sialm, and Zheng (2005):

$$ICI_t = \sum_{j=1}^{10} (w_{j,t} - \tilde{w}_{j,t})^2 \quad \text{(A1)}$$

where j=1 to 10, representing 10 different industries. $w_{j,t}$ is the portfolio weight of a mutual fund in industry j, and $\tilde{w}_{j,t}$ is the weight of industry j in the CRSP market portfolio. The 10-industry classification is provided in Appendix B of Kacperczyk et al. (2005).

A.2. GAP

Following Kacperczyk, Sialm, and Zheng (2008), we define fund return gap as:

$$GAP_{i,t} = \frac{1}{4}\sum_{k=0}^{3} (R_{i,t-k} - GR_{i,t-k}) \quad \text{(A2)}$$

where $R_{i,t\text{-}k}$ is the net return before expense for fund i in quarter t-k (k=0, 1, 2, 3). $GR_{i,t}$ is quarterly fund gross return as the buy-and-hold return on the beginning-of-quarter portfolio holdings:

$$GR_{i,t} = w_{s,t}\sum_{j=1}^{N} w_{i,j,t}R_{j,t} + w_{pb,t}R_{pb,t} + w_{c,t}RF_t \quad \text{(A3)}$$

where $w_{i,j,t}$ is the portfolio weight of fund *i* on stock *j*, calculated as the number of shares of stock *j* held by the fund multiplied by its market price, and then divided by the total stock holding value of the fund, with all variables involved measured at the beginning of quarter *t*. $R_{j,t}$ is the buy-and-hold return of stock *j* during quarter *t*. $w_{s,t}$ is the percentage of stock holding in the TNA of a fund, $w_{pb,t}$ is the percentage of preferred stock and bond holding in the TNA of a fund, and $w_{c,t}$ is the percentage of cash holding in the TNA of a fund. $w_{s,t}$, $w_{b,t}$, and $w_{c,t}$ are obtained from the CRSP. We set them missing if CRSP reports 0 for all these variables. $R_{pb,t}$ is the total return of the Lehman Brothers Aggregate Bond Index and RF_t is the risk-free return (yield on three-month Treasury bills, from CRSP) during quarter *t*.

A.3. SIMILAR

Based on Cohen, Coval, and Pastor (2005), we construct a variable SIMILAR to gauge the skill of a fund manager by the extent to which his stock holdings resemble those of funds with superior past performance. In each quarter, SIMILAR for fund i is:

$$\text{SIMILAR}_{i,t} = \sum_{j=1}^{J} w_{i,j}\delta_j \qquad \text{(A4)}$$

where there are I funds (i=1, …, I) and J stocks (j = 1, …, J). $w_{i,j}$ is the weight on stock j in manager i's portfolio at the end of each quarter and δ_j is the quality of stock j. δ_j can be measures as $\sum_{i=1}^{I} v_{i,j}\alpha_i$ where $v_{i,j} = \frac{w_{i,j}}{\sum_{i=1}^{I} w_{i,j}}$ and α_i is a fund's alpha estimated using the past twelve months fund return prior to the quarter.

A.4. EAR

Baker, Litov, Watchter, and Wurgler (2010) use the returns realized around the subsequent earnings announcements of stocks traded by mutual funds to measure fund managers' stock picking ability. Consistent with their approach, we estimate the earnings announcement returns (EAR) of fund *i* in quarter *t* as the difference between weighted earnings announcement returns of all stocks purchased and those of all stocks sold:

$$\text{EAR}_{i,t} = \sum_{j\in J+} \frac{w_{i,j,t-1} - \tilde{w}_{i,j,t-k-1}}{\sum_{j\in J+}(w_{i,j,t-1} - \tilde{w}_{i,j,t-k-1})} R_{j,t} - \sum_{j\in J-} \frac{w_{i,j,t-1} - \tilde{w}_{i,j,t-k-1}}{\sum_{j\in J-}(w_{i,j,t-1} - \tilde{w}_{i,j,t-k-1})} R_{j,t} \qquad \text{(A5)}$$

where i is the index for funds, from 1 to I, j is the index for stocks, from 1 to J, and k is either 1 (for funds reporting holdings at quarterly frequency) or 2 (for funds reporting holdings semi-annually). $w_{i,j,t-1}$ is the value of stock *j* held by the fund divided by the total value of stocks held by the fund and $\tilde{w}_{i,j,t-k-1}$, defined in Equation (3) of this paper, is the portfolio weight measured at the end of quarter t-1 under the assumption that the fund holds its positions, without trading, from its previous reporting date. J^+ = {j: $w_{i,j,t-1} - \tilde{w}_{i,j,t-k-1}$>0} denotes all stocks purchased by manager i in quarter t-1 and J^- = {j: $w_{i,j,t-1} - \tilde{w}_{i,j,t-k-1}$<0} denotes all stocks sold by fund i in quarter t-1. $R_{j,t+1}$ is the three-day event-window announcement return: $R_{j,t} = \sum_{-1}^{1} r_{j,\tau}$, where $r_{j,\tau}$ is the return of stock j from one trading day before to one trading day after the earnings announcement made in quarter t.

A.5. RPI

The reliance on public information (RPI) measure follows Kacperczyk and Seru (2007). For fund i in quarter t, it is the R-square of the following regression:

$$\%\Delta Hold_{i,j,t} = \beta_0 + \beta_{1,t}\Delta SR_{j,t-1} + \beta_{2,t}\Delta SR_{j,t-2} + \beta_{3,t}\Delta SR_{j,t-3} + \beta_{3,t}\Delta SR_{j,t-3} + \varepsilon_{j,t} \qquad \text{(A6)}$$

where $\%\Delta Hold_{i,j,t}$ is the percentage change in stock split adjusted holdings of stock j held by fund i from quarter t-1 to t. $\Delta SR_{j,t-1}$ to $\Delta SR_{j,t-4}$ are the four most recent changes in analysts' stock recommendations for stock j prior to the beginning of the period for measuring portfolio weight changes.

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Table 1: Summary Statistics for Sample Mutual Funds

This table reports the summary statistics for the sample of actively managed US equity mutual funds with Thomson Financial CDA portfolio holdings data and CRSP fund returns data. To be included in the analysis, the time interval between a fund's current and prior reporting dates must be within 6 months. Fund total net assets, annual return, turnover, expense ratio, and fund age are obtained from CRSP. Fund age is the number of years since fund organization. Information on the average and median numbers of stocks held by funds is from Thomson Financial. Percentage of funds with semiannual reporting is the number of funds with semiannual reporting divided by the total number of funds in each quarter. We average these fund characteristics across funds in each year and then report their time series means. We also report the snapshots in five years. The sample period is from 1990 to 2012.

	1990-2012	1990	1995	2000	2005	2012
Number of funds	2319	522	1170	1543	1232	1156
Aggressive Growth funds	232	101	161	178	146	142
Growth funds	1757	259	786	1122	903	851
Growth and Income funds	330	163	223	244	183	163
Total Net Assets ($ Millions)	730.29	244.78	402.58	690.88	915.65	968.8
Net Return (%/year)	9.59	-4.95	28.95	-1.43	7.29	14.49
Annual Turnover (%)	96.12	92.58	83.20	103.90	97.77	81.71
Annual Expense Ratio (%)	1.18	0.85	1.21	1.31	1.33	1.28
Fund Age (year)	9.64	7.60	5.47	5.89	7.06	11.16
# of stocks held – Mean	113	101	131	114	111	138
# of stocks held – Median	67	68	80	70	68	57
% of semiannual reporting funds	28.36	25.33	63.25	19.71	9.39	4.29

Table 2: Stock Returns across SUE-Sorted Deciles

This table reports the mean values of SUEs, number of stocks, and quarterly returns in the subsequent four calendar quarters (Q1-Q4) after portfolio formation, for each SUE-sorted deciles. The stock portfolios are formed either in the Stock Universe or in the sample of stocks held by funds. SUE of stock j reported in quarter t is defined as: $SUE_{j,t} = \frac{E_{j,t} - E_{j,t-4} - c_{j,t}}{\sigma_{j,t}}$, where $E_{j,t}$ is quarterly earnings (COMPUSTAT quarterly data item 8) *reported* during quarter t, $E_{j,t-4}$ is earnings *reported* four quarters ago. $c_{j,t}$ and $\sigma_{j,t}$ are the mean and standard deviation, respectively, of ($E_{j,t} - E_{j,t-4}$) over the preceding 8 quarters, with a minimum of 4 quarters required for the observation to be valid. The "Stock Universe" refers to all common stocks in the CRSP database with price greater than $1 and with non-missing standardized unexpected earnings (SUEs) computed using COMPUSTAT data. "Stocks Held by Funds" are those held by at least one of our sample funds at the end of a quarter. We also report the differences of stock returns between the top (P10) and bottom (P1) SUE stock deciles. The Fama-French three-factor alphas of return differences and the Carhart four-factor alphas of return differences. The table further reports the average of quarterly returns in the subsequent four quarters after portfolio formation for each stock-competition-sorted terciles for P10 and P1 stocks from fund held stocks. Inside the parentheses are the t-statistics. The sample period is from 1990 to 2012.

		Stock Universe					Stocks Held by Funds				
Stock Decile	SUE	Num of stocks	Q1	Q2	Q3	Q4	Num of stocks	Q1	Q2	Q3	Q4
P1	-3.96	413	2.13	2.75	3.32	4.60	308	2.28	2.62	2.95	4.07
2	-1.39	414	2.90	3.87	4.53	4.86	306	3.02	3.56	4.11	4.24
3	-0.75	414	3.46	4.48	4.69	4.73	304	3.44	4.17	4.27	4.17
4	-0.40	414	3.99	4.68	4.70	4.47	308	3.61	4.28	4.45	4.02
5	-0.14	414	4.53	4.56	4.80	4.59	311	4.40	4.34	4.58	4.11
6	0.10	414	4.56	5.00	4.78	4.93	310	4.24	4.64	4.48	4.57
7	0.36	414	4.65	4.89	5.07	4.79	308	4.39	4.46	4.86	4.35
8	0.70	414	5.11	4.97	5.13	4.69	306	4.68	4.68	4.62	4.10
9	1.27	414	5.39	5.20	4.72	4.58	306	5.10	4.63	4.29	4.10
P10	2.70	413	5.62	5.01	4.91	3.90	306	5.35	4.63	4.29	3.57
P10-P1			3.48	2.25	1.59	-0.70		3.07	2.01	1.34	-0.50
(t-stat)			(7.15)	(5.68)	(3.52)	(-1.61)		(6.38)	(3.54)	(2.23)	(-1.37)
3-factor alpha			3.47	1.36	1.41	-0.61		3.11	1.87	1.32	-0.46
(t-stat)			(5.82)	(4.46)	(2.70)	(-1.12)		(5.56)	(4.23)	(2.56)	(-0.63)
4-factor alpha			3.05	1.79	1.29	-0.75		2.51	1.55	0.92	-0.59
(t-stat)			(5.06)	(4.41)	(2.90)	(-1.26)		(4.93)	(4.14)	(2.43)	(-0.63)

Table 3: SUE Investing Measure: Statistics and Persistence

Panel A reports the summary statistics on the SUE investing measure (SIM, in percentage points) of the sample funds. In each calendar quarter t, we estimate the following measure: $\hat{SIM}_{i,t} = \sum_{j=1}^{N}(w_{i,j,t} - \tilde{w}_{i,j,t-k}) * (\frac{SUE_{j,t} - \mu(SUE_t)}{\sigma(SUE_t)})$ (k=1 or 2), where $w_{i,j,t}$ is the portfolio weights on stock *j* held by fund *i* reported within quarter *t*; $\tilde{w}_{i,j,t-k}$ is the hypothetical portfolio weights of stock j at the end of quarter t assuming the fund passively hold all positions from the end of quarter t-1 to quarter t. $SUE_{j,t}$ is the standardized unexpected earnings reported in quarter *t* for stock *j*. $\mu(SUE)$ and σ *(SUE)* are the cross-sectional mean and standard deviation of *SUE*s for all sample stocks in quarter t. SIM is the rolling 4-quarter average of $\hat{SIM}$ s from quarter t-3 to t. We calculate the summary statistics of SIM across funds in each quarter and then calculate time series averages. Panel B reports averaged $\hat{SIM}$ s (in percentage points) from Q1 to Q4 for fund deciles sorted on SIM in Q0. SIMs in Q0 are also reported. INACTIVE funds are the 10% of funds with SIM4closest to, and centered around, zero. The t-statistics in parentheses are computed using the Newey-West procedure with a 4-quarter lag. The sample period is from 1990 to 2012.

Panel A: SIM Statistics

	5%	25%	MEAN	MEDIAN	75%	95%	STD
			Panel A: SUE Investing Measures				
SIM (%)	-7.82	-1.72	1.29	0.97	3.81	10.79	5.78
(t-stat)			(5.74)	(4.32)			

Panel B: Persistence of Fund SIMs

SIM Ranking	SIM(Q0)	$\hat{SIM}$ (Q1)	$\hat{SIM}$ (Q2)	$\hat{SIM}$ (Q3)	$\hat{SIM}$ (Q4)
D1	-8.44	-2.10	-1.93	-1.96	-1.97
	(-22.11)	(-6.63)	(-4.30)	(-3.59)	(-4.75)
2	-3.44	-1.07	-1.08	-0.45	-0.95
	(-28.30)	(-2.94)	(-3.27)	(-0.62)	(-4.17)
3	-1.63	-1.01	-0.70	-0.60	-0.84
	(-17.56)	(-4.85)	(-3.11)	(-2.28)	(-4.28)
4	-0.42	0.07	-0.56	-0.52	-0.20
	(-4.81)	(0.30)	(-3.09)	(-2.69)	(-0.66)
5	0.56	0.53	-0.09	0.14	0.03
	(5.67)	(1.82)	(-0.45)	(0.50)	(0.12)
6	1.57	0.59	0.27	0.10	0.16
	(13.11)	(2.57)	(0.87)	(0.22)	(0.66)
7	2.81	0.91	0.74	0.34	0.74
	(19.33)	(2.32)	(1.87)	(1.09)	(2.59)
8	4.37	1.34	0.79	1.16	1.48
	(26.82)	(4.43)	(3.12)	(3.92)	(4.01)
9	6.68	2.37	2.36	2.36	1.98
	(33.14)	(7.80)	(5.45)	(6.59)	(6.23)
D10	12.94	4.05	3.40	3.51	3.88
	(45.02)	(8.90)	(7.39)	(7.54)	(7.47)
INACTIVE	0.00	0.15	-0.27	-0.31	-0.19
	(-0.07)	(0.50)	(-1.06)	(-2.96)	(-0.71)
D10-INACTIVE	12.94	3.90	3.67	3.82	4.07
(t-stat)	(45.22)	(8.72)	(7.56)	(7.87)	(8.03)

Table 4: Fund Performance across Decile Groups Sorted by SUE Investing Measures

This table reports the average performance of fund deciles sorted on SUE Investing Measures (SIMs). INACTIVE funds are the 10% of funds with SIM closest to, and centered around, zero. Fund performance measures include net returns, the Fama-French three-factor alpha, the Carhart four-factor alpha, and excess fund returns relative to two benchmark fund groups: SIZE-BM benchmarks and SIZE-BM-MOM benchmarks. Fund performance is measured for the quarter after initial fund ranking (Q1) and during the four quarters after initial ranking (Y1). Fund returns are in percentage points and measured before expense by adding proportional fund expense ratio back to after-expense fund returns reported in CRSP. The t-statistics in the parentheses are computed using the Newey-West procedure with a 4-quarter lag. The sample period is from 1990 to 2012.

	Net Return		Fama-French 3-Factor Alpha		Carhart 4-Factor Alpha		SIZE-BM Style-Adjusted Return		SIZE-BM-MOM Style-Adjusted Return	
SIM Decile	Q1	Y1	Q1	Y1	Q1	Y1	Q1	Y1	Q1	Y1
D1	2.54	11.08	0.15	0.68	0.07	0.28	-0.05	-0.31	-0.06	-0.23
	(2.76)	(5.79)	(1.02)	(0.30)	(0.32)	(0.41)	(-0.30)	(-1.45)	(-0.48)	(-1.06)
2	2.53	11.26	0.11	0.55	0.06	0.34	0.02	0.11	-0.02	-0.17
	(2.96)	(6.31)	(1.08)	(0.57)	(0.23)	(0.52)	(0.21)	(0.34)	(-0.32)	(-1.14)
3	2.49	10.18	0.07	0.32	0.12	0.36	-0.09	-0.32	-0.10	-0.05
	(3.00)	(6.29)	(1.22)	(0.27)	(0.96)	(0.71)	(-0.80)	(-1.09)	(-0.92)	(-0.28)
4	2.41	10.41	0.11	0.46	0.08	0.28	-0.07	-0.32	-0.04	-0.12
	(2.97)	(6.30)	(1.76)	(0.95)	(0.74)	(0.36)	(-0.83)	(-0.62)	(-0.67)	(-0.93)
5	2.41	10.57	0.03	0.10	-0.12	-0.33	-0.13	-0.43	-0.08	-0.27
	(2.69)	(5.91)	(0.15)	(0.43)	(-0.91)	(-0.92)	(-1.39)	(-1.31)	(-0.81)	(-1.48)
6	2.50	11.22	0.05	0.24	-0.03	-0.19	-0.14	-0.54	-0.06	-0.33
	(2.54)	(5.71)	(0.79)	(0.46)	(-0.26)	(-0.97)	(-1.31)	(-1.27)	(-0.72)	(-1.12)
7	2.65	11.99	0.08	0.58	0.05	0.24	-0.07	-0.31	-0.05	0.18
	(2.68)	(5.92)	(0.67)	(1.06)	(0.37)	(0.37)	(-0.90)	(-0.92)	(-0.53)	(1.19)
8	2.89	12.41	0.17	0.79	0.20	0.83	0.05	0.18	0.03	0.16
	(2.69)	(5.75)	(1.31)	(0.58)	(0.66)	(0.48)	(0.62)	(1.02)	(0.39)	(1.28)
9	2.83	12.15	0.22	0.71	0.21	0.89	0.08	0.35	0.07	0.28
	(2.57)	(5.87)	(1.69)	(0.95)	(0.62)	(0.42)	(0.76)	(0.67)	(0.54)	(1.44)
D10	2.98	11.92	0.57	1.78	0.35	1.38	0.16	0.56	0.12	0.37
	(2.58)	(5.63)	(2.29)	(1.86)	(1.21)	(-1.34)	(0.72)	(0.86)	(0.55)	(0.96)
INACTIVE	2.49	10.82	0.05	0.19	-0.04	-0.12	-0.13	-0.36	-0.06	-0.29
	(3.22)	(6.26)	(0.36)	(0.80)	(0.50)	(-0.61)	(-1.02)	(-1.09)	(-0.57)	(-1.60)
D10 – INACTIVE	0.49	1.1	0.52	1.59	0.39	1.5	0.29	0.92	0.18	0.66
	(1.41)	(1.38)	(1.58)	(1.35)	(1.59)	(1.30)	(0.95)	(1.51)	(1.19)	(1.23)

Table 5: Competition Investing Measure: Statistics and Persistence

Panel A reports the summary statistics for the competition indices of the sample funds. Panel B reports, for funds that are in the top SIM4 decile in Q0 that are further sorted into terciles by the 4-quarter rolling average CIM in Q0, the averaged single quarter competition index, $\widehat{CIM}$ and the percentage of funds in different SIM deciles during Q1 to Q4. The t-statistics in parentheses are computed using the Newey-West procedure with a 4-quarter lag. The sample period is from 1990 to 2012.

Panel A: CIM Statistics

	5%	25%	MEAN	MEDIAN	75%	95%	STD
CIM(%)	-0.08	1.10	2.37	2.13	3.63	5.33	1.74
(t-stat)			(4.92)	(4.86)			

CIM Rank in Q0	SIM Decile Rank in Subsequent Quarters	Q1 $\widehat{CIM}$/PCT(%)	Q2 $\widehat{CIM}$/PCT(%)	Q3 $\widehat{CIM}$/PCT(%)	Q4 $\widehat{CIM}$/PCT(%)
	D1-D5	0.55/28.89	0.67/28.29	0.81/29.51	0.66/27.76
	D6-D7	0.82/17.24	1.01/16.19	0.79/16.61	0.65/17.28
T1 (Low)	D8-D9	0.95/30.71	0.99/31.10	1.09/29.26	0.93/29.25
	D10	1.12/23.16	1.13/24.42	1.28/24.62	1.17/25.72
	D1-D5	2.47/30.81	2.47/35.71	2.65/31.70	2.43/31.12
	D6-D7	2.90/14.11	3.04/12.22	2.61/14.30	2.15/15.18
T2 (Medium)	D8-D9	2.67/24.33	2.69/23.62	2.70/26.38	2.52/32.34
	D10	2.55/30.75	2.72/28.45	2.74/27.63	2.58/21.36
	D1-D5	4.98/30.18	4.82/31.83	4.45/34.08	4.19/33.87
	D6-D7	5.52/12.98	5.57/13.16	5.73/14.16	5.37/13.23
T3 (High)	D8-D9	4.92/29.09	5.18/27.36	4.95/26.44	5.09/25.53
	D10	4.91/27.76	4.97/27.65	5.23/25.32	5.04/27.37
		Diff(t-stat)	Diff(t-stat)	Diff(t-stat)	Diff(t-stat)
	D1-D5	4.65(12.56)	4.43(12.37)	4.27(11.39)	4.20(11.60)
T3-T1	D6-D7	5.55(14.23)	5.02(15.59)	5.27(13.51)	5.40(13.09)
	D8-D9	4.56(12.23)	4.91(11.94)	4.55(12.60)	4.85(12.88)
	D10	4.34(12.17)	4.59(12.15)	4.44(10.30)	4.32(10.92)

Table 6: Fund Performance across CIM Terciles of the Top SIM Funds

This table reports the average fund performance for top SIM-decile funds in tercile groups sorted by the competition measure CIM. T1 funds have the lowest CIM and T3 funds have the highest CIM. The t-statistics in the parentheses are computed using the Newey-West procedure with a 4-quarter lag. The sample period is from 1990 to 2012.

	Net Return		Fama-French 3-Factor Alpha		Carhart 4-Factor Alpha		SIZE-BM Style-Adjusted Return		SIZE-BM-MOM Adjusted Return	
CIM	Q1	Y1	Q1	Y1	Q1	Y1	Q1	Y1	Q1	Y1
T1 (Low)	3.31	13.23	0.83	2.65	0.67	2.04	0.51	1.75	0.57	1.87
	(2.76)	(6.21)	(2.55)	(2.69)	(2.39)	(2.36)	(1.93)	(2.49)	(2.33)	(2.58)
T2	2.75	11.35	0.57	1.62	0.28	1.23	0.12	0.39	-0.15	-0.53
	(2.72)	(5.84)	(1.97)	(1.83)	(1.09)	(1.85)	(1.18)	(1.84)	(-1.96)	(-1.72)
T3 (High)	2.79	11.16	0.31	1.09	0.14	0.89	-0.15	-0.46	-0.06	-0.24
	(2.62)	(5.3)	(1.92)	(1.57)	(0.96)	(1.92)	(-1.47)	(-1.92)	(-0.72)	(-0.81)
T1-T3	0.52	2.07	0.52	1.56	0.53	1.15	0.66	2.21	0.63	2.11
	(2.25)	(1.92)	(2.11)	(2.47)	(2.56)	(1.86)	(2.16)	(2.34)	(2.37)	(2.59)

Table 7: Regression Analysis of Fund Performance: Controlling for Fund Skills

This table reports the average coefficients from Fama-MacBeth regressions of before-expense fund returns (in percentage points) of quarter Q1 and year Y1. PSIM equals SIM if SIM is positive, and zero otherwise. NSIM equals SIM if SIM is non-positive, and zero otherwise. T1, T2, and T3 are dummy variables for top SIM-decile funds being in the low, middle, and high competition index (CIM) tercile, respectively. SIZESCORE, BMSCORE, and MOMSCORE are measures of fund investment styles based on size, book to market ratio, and momentum, as defined previously. ICI, GAP, SIMILAR (pre-multiplied by 100), EAR, and RPI are fund skill characteristics defined in the Appendix. These measures are in percentage points. FEE is the fee charged by a fund. FUNDTURN is the turnover ratio of a fund. TNA is the logarithm of fund total net assets. FAMTNA is the logarithm of fund family TNA. AGE is the logarithm of fund age. FLOW is the net fund flow during Q0. STDEV is the standard deviation of fund net return in the previous year. All explanatory variables are measured at the end of Q0. The t-statistics in parentheses are computed using the Newey-West procedure with a 4-quarter lag. The sample period is from 1990 to 2012.

	Q1	Y1	Q1	Y1
INTERCEPT	3.97	14.81	2.82	10.76
	(3.84)	(5.12)	(3.18)	(4.53)
PSIM	0.10	0.23	0.06	0.16
	(1.72)	(1.56)	(1.57)	(1.38)
NSIM	0.04	0.05	0.02	0.04
	(0.57)	(0.73)	(0.53)	(0.64)
T1	0.74	2.55	0.68	2.39
	(3.60)	(3.77)	(3.23)	(3.45)
T2	0.36	1.49	0.39	1.25
	(1.35)	(1.43)	(1.24)	(1.04)
T3	-0.20	-0.62	-0.11	-0.26
	(-1.53)	(-1.48)	(-1.28)	(-1.10)
SIZESCORE			0.02	0.03
			(0.76)	(0.85)
BMSCORE			-0.01	-0.03
			(-0.56)	(-0.88)
MOMSCORE			0.03	0.06
			(1.14)	(1.54)
ICI			1.36	2.89
			(1.93)	(2.42)
GAP			0.86	2.28
			(2.03)	(2.71)
SIMILAR			2.24	6.42
			(4.22)	(4.4)3
EAR			7.39	27.42
			(1.17)	(1.45)
RPI			-1.95	-2.03
			(-2.03)	(-2.27)
FEE			-11.18	-50.33
			(-2.24)	(-2.36)
FUNDTURN			0.18	0.72
			(1.20)	(1.43)
TNA			-0.23	-0.42
			(-1.98)	(-2.49)
FAMTNA			0.05	0.10
			(1.43)	(1.82)
AGE			0.10	-0.19
			(0.52)	(-1.22)
FLOW			1.76	-1.09
			(1.92)	(-1.27)
STDEV			16.35	54.32
			(1.45)	(1.62)
Adj R^2	0.06	0.08	0.34	0.36

Table 8: Liquidity Characteristics of Fund Holdings across Competition Index (CIM) Terciles

This table reports average liquidity characteristics of fund holdings in the ranking quarter Q0 across fund terciles sorted by the competition index CIM. In each quarter we first identify the top decile of funds based on SIM. Then, within this subset of funds we further sort funds into terciles based on the competition index CIM. The liquidity characteristics of fund holdings are the weighted averages of liquidity characteristics of stocks a fund holds. STDR is the average annualized standard deviation of daily stock returns in Q0 of stocks held by fund. IDIORISK is the average annualized standard deviation of the residuals in the regression of daily stock returns on the three Fama-French factors, measured during quarter Q0. STKTURN is the quarterly cross-sectional percentile rank of daily turnover, ranked for NYSE/AMEX and NASDAQ separately. ILLIQ is the quarterly cross-sectional percentile rank of the illiquidity measure defined in Amihud (2002), ranked for NYSE/AMEX and NASDAQ separately. 1/P is the inverse of stock price at the beginning of a quarter. DY (%) is a stock's dividend yield. S&P represents a stock having S&P500 membership. R2 is the R-square of regressing monthly returns of past 36 months onto the NYSE index. P-RATIO is the stock price at the beginning of the period divided by the price six months ago, minus one. NASDAQ is a dummy variable for Nasdaq stocks. SIZE is the average market cap (in $thousands) at the beginning and end of the period. ZERO is a dummy for zero daily return for a stock. %S&P, %NASDAQ, and %ZERO are the fraction of stocks having S&P500 membership, being listed in NASDAQ, and having zero daily stock returns. We first compute the fund-level average values of the liquidity characteristic weighted by fund portfolio weights, and then obtain the average characteristics within each fund tercile. The t-statistics in parentheses are computed using the Newey-West procedure with a 4-quarter lag. The sample period is from 1990 to 2012.

Rank	STDR	IDIORISK	STKTURN	ILLIQ	1/P	DY (%)	%S&P	R2	P_RATIO	%NASDAQ	SIZE	%ZERO
T1	2.73	2.06	68.91	12.88	0.044	0.27	0.32	0.20	0.18	0.34	10.60	6.50
T2	2.53	2.01	71.77	11.65	0.030	0.28	0.42	0.22	0.19	0.33	19.28	5.43
T3	2.46	1.83	71.97	9.54	0.029	0.35	0.56	0.26	0.21	0.35	34.75	4.53
T3-T1	-0.27	-0.23	3.05	-3.34	-0.014	0.08	0.24	0.06	0.03	-0.01	24.15	-1.97
(t-stat)	(-3.72)	(-3.76)	(3.89)	(-10.54)	(-9.58)	(2.57)	(7.43)	(6.30)	(3.31)	(-0.79)	(7.24)	(-5.36)

Figure 1: Time Series of Stock-level Profitability

This figure plots the return difference between top and bottom SUE decile stock portfolios in each holding period. In each calendar quarter t-1, we rank "fund-held stocks" into deciles based on SUEs. We compute decile portfolio returns in the calendar quarter t and then compute return differences between the top and bottom SUE deciles in each holding quarter and average them within a calendar year to obtain the annual return difference for the holding period. Vertical bars are the return difference between the top and bottom portfolios sorted on stock SUEs. The curve is the 3-year moving average of return differences between top and bottom SUE decile portfolios.

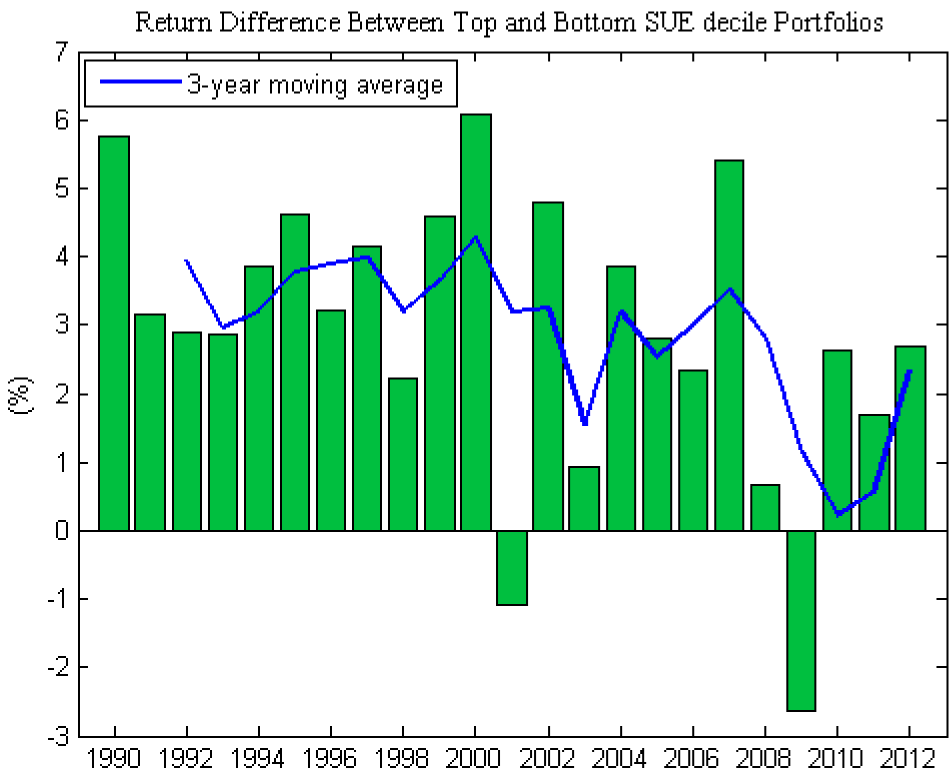
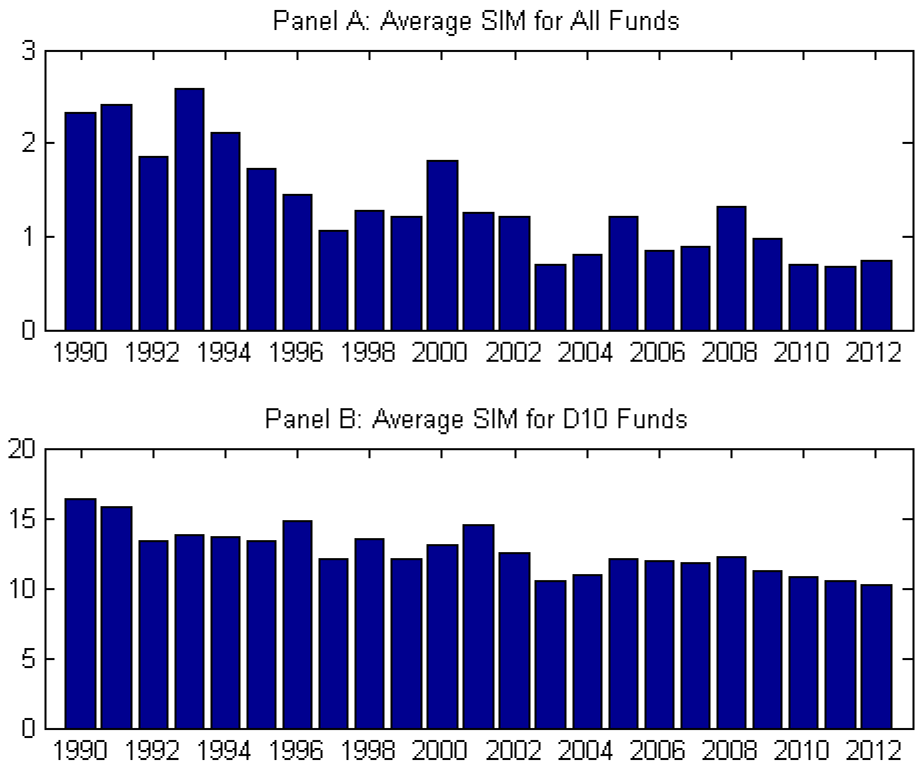
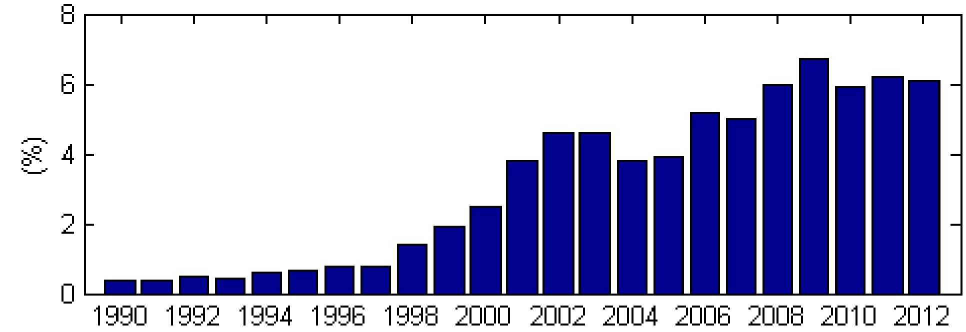


Figure 2: Time Series of SUE Investing Measure (SIM) and Competition Index (CIM)

Panel A plots the time series of average SUE investing measure (SIM) across all funds. Panel B plots the time series of average SIM for funds in the top SIM decile (D10 funds). Panel C plots the time series of CIMs for the top SIM-decile funds. Panel D plots the time series of the average CIMs for the T1 (bottom tercile) and T3 (top tercile) funds within D10 funds. For all plots, we first calculate the average measures for each fund group in each quarter and then average them within each calendar year to obtain the time series.



Panel C: Average CIM for All Funds



Panel D: Average CIM for T1 and T3 Funds