Does Learning from Academia Help?

Anomaly Exploitation and Mutual Funds Performance*

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Abstract

Mutual funds generally exhibit limited exploitation of anomalies, as noted by Edelen et al. (2016). We provide a refined perspective on this issue and propose a new measure of skill, *Learning Ability (LA)*, motivated by the increase in anomaly-related positions following academic publications. We demonstrate that mutual funds engage in persistent learning activities, with their learning ability significantly predicting better performance. Specifically, funds in the top quintile of *LA*-sorted portfolios outperform the lowest *LA* funds by an annual alpha of 2%. Furthermore, we document a positive relation of learning ability and future fund flows. Our findings suggests that a subset of mutual funds effectively assimilate insights from academia and achieve superior performance.

1. Introduction

Anomalies provide a statistically reliable means to achieve performance that exceeds standard benchmarks. Despite this potential, research indicates that institutional investors generally struggle to leverage this predictability in equity returns (Lewellen, 2011; Akbas et al., 2015; Edelen et al., 2016). Calluzzo et al. (2019) attribute this phenomenon to information shocks and the dissemination of knowledge through academic publications. They find that following the publication of anomalies, there is a significant increase in institutional trading. However, this increase is particularly pronounced among hedge funds and transient institutions, while similar effects in mutual funds remain notably absent.

It is widely documented that US mutual funds fail to generate positive risk-adjusted returns (Gruber, 1996; Fama and French, 2010). As the major component of professional investors, why do mutual funds seem to take so little advantage of anomalies to enhance performance (Ke and Ramalingegowda, 2005; Ali et al., 2008), even in the post-publication periods (Calluzzo et al., 2019)? Possible reasons include that mutual funds typically undertake long-only positions and face restrictions on trading small stocks due to regulatory and fiduciary constraints (e.g., Del Guercio, 1996; Falkenstein, 1996; Broman and Moneta, 2024). Additionally, fund managers' ability to assimilate and respond to new insights may further limit their capacity to exploit these opportunities.

In this context, we propose a new measure of mutual fund ability, which is constructed based on the event of the anomaly's initial publication in the academic literature. We view journal publication as a shock that increases knowledge regarding the existence and profitability of the anomaly trading strategy (Calluzzo et al., 2019). Information is core in efficient capital markets. According to Grossman and Stiglitz (1980), sophisticated investors earn alphas by engaging in costly searches for new information and processing it accurately and promptly. Inspired by these discussions, we introduce a measure that encapsulates a mutual fund's propensity to learn about and exploit newly-published trading opportunities, which we term "learning ability".

Utilizing a sample of 202 anomalies spanning the past 40 years, we rank stocks each quarter according to the published "anomaly variables" and construct a fund-anomaly level *Anomaly Investing Measure (AIM)* as the weighted average of the anomaly decile ranks of individual stocks held by a mutual fund. We determine whether a fund learns from a particular anomaly (hereinafter referred to as *L(t)*, or *Probability of Learning*) by conducting a statistical t-test to assess whether the pre- and post-publication *AIMs* differ significantly around the month of publication. The fund-level *Learning Ability (LA)* is then computed as the average of *L(t)* across all published anomalies. Our findings indicate that funds with higher *LA* exhibit lower expense and turnover ratios, and tend to be larger and younger. Among the wide array of anomaly characteristics, "Trading", "Analyst" and "Options" signals are the most widely learned by mutual funds after publication. Furthermore, the learning action demonstrates strong persistence: if a fund learns from anomalies in one period, it has a 7.2% higher probability of learning in the next publication month. This effect remains evident through the fourth month following the anomaly's publication.

We then provide strong evidence of managerial skill stemming from anomaly exploitation by documenting predictability in fund performance. Funds in the top quintile of *LA*-sorted portfolios outperform those in the lowest *LA* quintile by an economically significant 0.156% per month (or 1.87% per annum) in Carhart 4-factor alphas (Fama and French 1993; Carhart 1997), with statistical significance at 1% level. To better understand the sources of this cross-sectional variation, we decompose fund performance as outlined by Daniel et al. (1997) and find that most of the outperformance of high *LA* funds is attributable to their superior stock-picking abilities.

This significant *LA*-performance relation is robust after controlling for common fund characteristics, such as fund size, age and expense, etc. We also regress different measures of future fund performance on both *LA* and other skill proxies, including Return Gap (Kacperzczyk, Sialm and Zheng, 2008), Industry Concentration Index (Kacperczyk et al. 2005), Active Share (Cremers and Petajisto 2009), and R-square (Amihud and Goyenko 2013). In all specifications, our measure carries a positive and significant coefficient. An increase of one standard deviation in *LA* significantly raises annualized Carhart 4-factor alpha by 0.12 to 0.18 percentage points, with different skill proxies included as independent variables. When considering the time variations in the predictive relation, we find that the predictive power of *LA* on future fund performance primarily arises during periods with higher average anomaly return and market sentiment.

We further examine the relation between the learning ability and mutual fund flows. We expect that higher *LA* will lead to increased future fund flows so that the managers could be motivated to learn from academia and trade following the anomalies to obtain better compensation, despite the associated learning costs. Our results confirm this expectation, and this positive relation remains robust even when controlling for various fund characteristics and other skill proxies.

Our work differs from the previous studies such as Kacperczyk et al. (2005), Cremers and Petajisto (2009), Avramov et al. (2020), in at least three aspects: First, we focus on the dynamic changes in mutual fund holdings, which we believe reflect fund managers' ability to search for and process timely information, rather than merely examining the static structure of their positions. Second, our measure utilizes academic publications as shocks to managers' information sets. This event-study style methodology helps set apart alternative explanations and identify skilled managers.[1] Lastly, we employ a broader set of anomalies published in more than 120 academic papers to better encompass the publication signals faced by mutual fund investors.

Our findings complement recent discussions on how institutional investors trade anomalies and adjust their portfolios by learning potential trading opportunities from academic research. In aggregate, institutions are shown to take little advantage of anomalies and even trade contrary to anomaly prescriptions (Lewellen, 2011; Edelen et al., 2016). However, Calluzzo et al. (2019) argue that these results are driven by trading in the pre-publication period. They also document an increase in institutional trading following the academic publication of anomalies. Furthermore, anomaly-based trading tends to vary across different types of institutions. Calluzzo et al. (2019) find that this phenomenon is more pronounced among hedge funds and institutions with high turnover. Ke and Ramalingegowda (2005) observe that transient institutional investors trade to exploit the post-earnings announcement drift (PEAD). In the context of mutual funds, Ali et al. (2008) find that few funds trade on accruals anomaly. Similarly, Akbas et al. (2015) and Edelen et al. (2016) demonstrate that funds do not effectively exploit predictability in the cross-section of equity returns. Nonetheless, our study provides evidence that mutual funds, or at least some of them, do exploit anomalies around academic publications and get superior performance.

Our paper adds to the huge literature on fund investment skill. Academics and analysts have documented numerous methods for selecting funds (see, Kacperczyk et al., 2005; Cohen et al., 2005; Kacperczyk and Seru, 2007; Kacperczyk et al., 2008; Cremers and Petajisto, 2009; Amihud and Goyenko, 2013; Agarwal et al., 2014, etc.). Hinted by discussions on anomaly publication and institutional trading, such as Calluzzo et al. (2019), we propose a new proxy for assessing the learning ability of mutual fund managers. Given the mixed evidence regarding whether mutual funds represent "smart money" or "dumb money" (e.g., Berk and Van Binsbergen 2015; and Akbas et al. 2015), our work contributes to the longstanding debate whether mutual fund managers are skilled investors.

We also expand upon the anomaly-related literature. Over the past decades, academia has identified more than 400 anomalies (e.g., Hou et al., 2020). However, these anomalies do not

[1] It has been questioned that whether the vast number of performance measures actually capture managerial skills. As suggested by Dybvig and Ross (1985), to condition returns on information sets serves as a remedy.

always persist, and the cross-sectional predictability of anomaly signals can decline by over 50% once they are published (McLean and Pontiff, 2016). Bowles et al. (2024) show the impact of the publication of anomaly trading signals on anomaly returns. The dynamics of anomaly returns indicate that market participants do react to such information. In this paper, we provide more direct evidence from the perspective of mutual funds. Utilizing more than 200 anomalies published over past 40 years, we examine to what extent these anomalies have been known and exploited by mutual funds.

2. Variable Construction and Data Description

2.1 Learning Ability Measure

We take three steps to assess a fund's learning ability. First of all, we quantify the extent to which a fund engages in anomaly-based trading by conducting a series of *Anomaly Investing Measure (AIM)* following methodologies similar to Avramov et al. (2020). For each anomaly documented in previous studies, we assign directional signs to the corresponding firm characteristics and rank the stocks quarterly, categorizing them into ten distinct groups, with higher ranks indicating an expectation of superior future returns. *AIM* is calculated as the value-weighted average of the anomaly decile ranks of individual stocks held by the mutual fund, minus the average ranks implied by the benchmark portfolio. In particular, using the most recently reported portfolio holdings of fund *f* in quarter-end *q*, we define the *AIM* for anomaly *j* as follows:

$$AIM_{f,q}^{j} = \sum_{i}(w_{i,f,q} - w_{i,b,q})Decile_{i,q}^{j}, \tag{1}$$

where $Decile_{i,q}^{j} \in \{1,2,\dots,10\}$ is the decile rank of stock *i* based on anomaly *j* in quarter-end *q*, $w_{i,f,t}$ and $w_{i,b,t}$ are portfolio weight of stock *i* in fund *f* and in its index benchmark *b*. We define the index benchmark for each fund as the one that exhibits the smallest discrepancy from the actual fund holdings, as Sensoy (2009) shows that a mutual fund's self-stated benchmark may differ from its actual investment benchmark. Here, despite the traditional long-only feature of mutual funds, we calculate the weight, or the relative long or short positions, as the deviation of fund holdings from the investment weights implied by their benchmark portfolio. This helps us to measure how much they tilt their portfolios toward certain anomaly characteristics. Assuming there are J anomalies, we can calculate J *AIMs* accordingly.

AIM has a clear economic interpretation, as it measures the similarity between the active portion of a fund's portfolio and the anomaly long-short portfolio. As discussed in Cremers and

Petajisto (2009), any portfolio can be decomposed into a 100% position in its benchmark index plus a zero-net-investment long-short portfolio on top of that. When constructing *AIM*, we focus on this active long-short portfolio as it is the part that reveals the ability of active management. The *AIM* measure indicates the extent to which a fund engages with an anomaly strategy and is consistent with those utilized in Avramov et al. (2020) and Broman and Moneta (2024). A higher value of *AIM* for a particular anomaly reflects a more active tilt towards that anomaly.

In the second step, we focus on the dynamic changes in *AIMs* around the publication. Previous literature documents that mutual funds often hold overpriced stocks (e.g., Edelen et al., 2016). If this occurs due to a lack of awareness, we expect that funds with strong information-searching and processing abilities would begin to adopt anomaly strategies once they are published. Hence, a fund is more likely to be considered as "learning from academia" if its *AIM* increases significantly and promptly after the paper is released. To analyze how fund trading behavior shifts around the publication, we conduct a time series regression for each anomaly and each fund, using *AIM* for that anomaly as the dependent variable and a dummy variable *Post* as the independent variable. The analysis window spans three years before and after the publication month. We require at least two observations before and after the publication for each fund to avoid potential bias. We take the t-statistics of the *Post* dummy and apply the following function to transform them into a continuous measure *Probability of Learning L(t)*:

$$L(t) = Max(0, 2\Phi(t) - 1) = Max(0, 1 - 2\alpha(t)), \qquad (2)$$

where $\Phi(t)$ is the standard normal cumulative distribution function and $\alpha(t)$ is the significance level corresponding to *t*, indicating the probability of rejecting the null hypothesis that the *Post* dummy has a coefficient greater than zero. A lower confidence level suggests that the fund is more likely to have followed the anomaly strategy proposed by academic research. However, some funds may have already adopted the anomaly strategy before the publication and might have adjusted their strategy due to potential decay in the anomaly's profitability once it became widely known. Consequently, a negative *t* could result from either poor learning ability or prior knowledge. To avoid penalizing these knowledgeable funds, we treat all funds with nonpositive *t*-values equally by taking the maximum of zero and $1 - 2\alpha$. Figure 1 shows the relation between the *t*-value and *L(t)*, indicating that *L(t)* ranges from 0 to 1, increases with the *t*-value, and equals zero when $t \leqslant 0$.

Finally, the fund-level *Learning Ability (LA)* could be calculated as the average *L(t)* across all the anomalies observed in the past. Since a single paper may contain multiple anomalies in the

CZ dataset, we retain only the anomaly with the highest *L(t)* to avoid over-weighting papers with numerous anomalies. In this sense, the *Learning Ability (LA)* for fund f at quarter q is defined as:

$$Learning\ Ability_{f,q} = \frac{1}{N_q} \sum_{j=1}^{N_q} L(t_f^j), \quad (3)$$

where $L(t_f^j)$ is the fund *f*'s probability of learning from the anomaly *j*, and N_q denote the number of anomalies used for calculation in quarter-end *q*. It is worth mentioning that we employ a [-3, +3] year window to estimate the degree of learning, which may incorporate future information and thus cause looking-forward bias. To avoid overlap between the estimation and prediction periods, an anomaly is included in the calculation of *LA* only after it has been published for three years. To mitigate the impact of random factors, *LA* is calculated only when N_q is three or more. This requirement leads to the exclusion of early data, ensuring that only funds with a sufficiently extended history are considered for analysis.

[Figure 1 about here.]

2.2 Data and Sample

We form our main dataset by merging three databases, namely, the Center for Research in Security Prices (CRSP) Survivorship Bias Free Mutual Fund Database, the Thomson Financial Mutual Fund Holdings, and the Open Asset Pricing dataset by Chen and Zimmermann (CZ, 2022). The CRSP Mutual Fund Database provides information about mutual fund returns, expenses, net asset value (NAV), total net assets (TNA) and other fund characteristics. We combine multiple share classes into a single fund. We calculate the TNA of each fund as the sum of the TNAs of its share classes and calculate fund age as the age of its oldest share class. For other fund characteristics, we used a TNA-weighted average across the share classes. We obtain quarterly mutual fund portfolio holdings data from the Thomson Reuters Mutual Fund Holdings S12 database. Using MFLINKS files from the Wharton Research Data Services (WRDS), we link the mutual fund holdings data to CRSP dataset.

The firm-specific characteristic variables related to market anomalies are drawn from CZ dataset which replicates the predictors of stock return cross-sections and validates the predictability found in most samples from the original studies.[2] It has been utilized in several related works (e.g., Chen and Zimmermann, 2020; Chen, 2021; Muravyev et al., 2022), lending it credibility and accuracy. The dataset's documentation includes only the year of publication. To obtain the precise

[2] The Chen and Zimmerman (2022) anomalies data are available at https://www.openassetpricing.com/.

publication time, we manually collected the publication month for each paper. The version used in our paper is August 2023 release (v1.3.0), which contains 212 predictors and 113 placebos. We narrow our focus to 202 anomalies published across 124 papers for three primary reasons:

(1) We remove 83 anomalies due to missing signs in the dataset's documentation file;

(2) Mutual fund holding data begins from 1980Q1, allowing us to utilize only anomalies published after 1983;

(3) As mentioned earlier, we rank anomalies into 10 deciles, necessitating sufficient dispersion in firm characteristics. Specifically, we calculate the minimum, 25th percentile, median, 75th percentile, and maximum values for each firm characteristic, considering only those anomalies that exhibit distinct values across these five metrics.

The earliest and latest publication dates among the anomalies we use are June 1984 and November 2016, respectively. We then associate portfolio holding with these 202 anomaly decile ranks. Our analysis focuses on domestically active-managed equity funds; therefore, we apply several filters to the data. Following Kacperczyk et al. (2008) and Doshi et al. (2015), we select funds with certain Lipper classification codes or other target codes available in the CRSP mutual fund database.[3] We exclude passive funds (including ETFs) since we believe our measure works best for managers whose investment decisions are information-sensitive. We follow the methodologies of Dannhauser and Pontiff (2024) and Ben-David et al. (2022) to identify passive index funds in the CRSP Mutual Fund database, with slight modifications to their approaches. A fund is identified as an index mutual fund if at any point in fund history it is flagged by the (1) name search[4], or (2) a CRSP index fund flag equal to D or B, and (3) is not flagged as an ETF[5]. We search each fund name to eliminate target date funds[6], leveraged and inverse funds[7]. Fund-level

[3] We select the funds with Lipper classification codes of EIEI, G, LCCE, LCGE, LCVE, MCCE, MCGE, MCVE, MLCE, MLGE, MLVE, SCCE, SCGE, SCVE, or Lipper target codes of CA, EI, G, GI, MC, MR, SG. If Lipper classification and target codes are missing, we include funds with Strategic Insight target codes of AGG, GMC, GRI, GRO, ING, SCG. In the absence of these codes, we select funds with Wiesenberger target codes of G, G-I, GCI, IEQ, LTG, MCG, SCG.

[4] Index funds are flagged if index_fund_flag is not missing or the CRSP fund name contains the following strings: SP, DOW, Dow, DJ or if the lowercase version of the CRSP fund name contains: index, idx, indx, composite, nyse, nasdaq, s&p, s and p, s & p, 50, 100, 200, 400, 500, 600, 1000, 1500, 2000, 2500, 3000. These numbers are selected based on major U.S. stock indices. We manually check some funds whose names include 'Morningstar', 'Wilshire', 'Bloomberg', 'FTSE', etc., and find that almost all can be absorbed by existing filters.

[5] Broad ETF products are flagged if et_flag is not missing or the CRSP fund name contains the following strings: ETF, ETN or if the lowercase version of the CRSP fund name contains: ishares, exchange traded, exchange-traded.

[6] Target date funds are flagged if the lowercase version of the CRSP fund name contains: target, retirement, 2010, 2015, 2020, 2025, 2030, 2035, 2040, 2045, 2050, 2055, 2060, 2065. These numbers are selected based on S&P target date indices.

[7] Inverse and leveraged funds are identified if the lowercase version of their name contains the following strings: inverse, ultra, 1.5x, 2x, 2.5x.

variables are constructed in the same way as in the sample of active funds. Finally, we exclude observations on funds that allocate less than 80% or more than 105% of their portfolio to stocks in the current quarter. We also eliminate the first two years of return data to eliminate incubation bias (Evans, 2010), and exclude funds with total net assets (TNA) below $10 million or fewer than 10 stock holdings.

To control for the effects of fund characteristics, we include total net assets (TNA), fund age in month (Age), fund expense ratio (Expense), fund turnover ratio (Turnover), net inflow (Flow) and return of the last quarter (Past Return). In addition, to ensure that our *LA* measure is different from other managerial skill proxies documented in the literature, our empirical investigations also consider Return Gap (Kacperzczyk, Sialm and Zheng, 2008), Industry Concentration Index (Kacperczyk et al., 2005), Active Share (Cremers and Petajisto, 2009), and R-square (Amihud and Goyenko, 2013). Detailed descriptions of all variables are provided in Appendix A.

[Table 1 about here.]

Our final sample includes 92,245 fund-quarter observations and 2,485 unique actively managed mutual funds. Table 1 includes statistics on the parameters and variables of interest. By definition, estimated values of our *Learning Ability (LA)* measure is between 0 and 1. As shown in Panel A, the pool mean of *LA* is 0.482, which is equivalent to an average *t*-value of 0.646, reflecting the improvement in investment in a certain anomaly after its publication. The correlation table, Panel B of Table 1, shows that *LA* is higher for larger (higher TNA), younger funds and funds with higher expense ratio. A detailed analysis of the determinants of *LA* appears in next section.

3. Stylized Patterns of Fund Learning Ability

3.1 Learning Ability and Fund Characteristics

Utilizing fund characteristics and other skill proxies in the previous literature, Table 2 reports the results of multivariate Fama-MacBeth (1973) regressions of the fund's *Learning Ability (LA)* on a set of control variables lagged by one quarter. Consistent with Table 1, funds with higher *LA* display lower expense and turnover ratio, and tend to be larger and younger funds. As the learning activity might relate to the performance of anomalies in general, we include the average anomaly returns in the regression. Besides, as the features of manager team might influence the learning activity of funds, we further consider the impact of managers' tenure and team management. Controlling for these fund characteristics, we find a significant positive relation between *LA* and average anomaly return, as well as the average tenure of managers in charge. One percentage point (percentage) increase of anomaly return (tenure) relates to 0.010 (0.007) increase in *LA*. As for the existing skill proxies in the previous literature, *LA* is significantly and positively correlated with Active Share, but, interestingly, negatively correlated with Return Gap measure. The relations between *LA* and ICI or R2 are not significant. This reflects different construction logic and incremental information content of our measure compared with other skill proxies.

[Table 2 about here.]

3.2 Learning across Anomaly Categories

Now we turn to the heterogeneity analyses in mutual fund learning. In the previous section, we put all published anomalies together to construct a fund-quarter level measure *Learning Ability (LA)*. Here we utilize the fund-anomaly level measure *Probability of Learning* $L(t)$ as defined in section 2.2.1. As there is a large spectrum of anomaly characteristics, it would be interesting and relevant to explore the learning activities across different anomaly categories.

According to the open-source asset pricing dataset (Chen and Zimmerman, 2022), anomalies are divided into eight categories based on their constructing methods and related characteristics: "Accounting", "Analyst", "Event", "13F", "Price", "Trading", "Options" and "Others". As shown in the second column of Table 3, the number of "Accounting" anomalies takes up more than half of our final sample (105 in 202 anomalies), following which is "Price" anomalies (42), "Trading" anomalies (18) and "Analyst" anomalies (12).[8] For each anomaly categories, we calculate the average of $L(t)$ across all funds. The results are shown in the third column of Table 3. We also compute a similar binary measure: *Binary L(t)=1* if *L(t)* is larger than 0, and 0 otherwise. The average of the binary measure is reported in the last column.

In each anomaly category, the average levels of *L(t)* and *Binary L(t)* are similar. Anomalies based on "Trading", "Analyst" and "Options" signals are most widely learned by mutual funds after publication, with average (*Binary*) *L(t)* values of 46%, 44% and 43% (56%, 59% and 58%) respectively. Following these three anomaly categories are "Accounting" and "Price" anomalies, as well as anomalies that are difficult to classify and fall into "Other". Then the minority anomalies in "13F" and "Event" are the least learned ones, with average (*Binary*) *L(t)* values of 13% and 15% (13% and 9%) lower than "Trading" ("Analyst") anomalies, respectively. Compared with the mean

[8] This distribution might differ from the original anomaly sample due to our screening process as described in Section 2.2.1.

value 0.48 of fund-quarterly level Learning Ability measure, the results indicate that "Trading", "Analyst" and "Options" anomalies are more attributable for the fund learning activities.

[Table 3 about here.]

3.3 The Persistence of Learning

As we consider the average learning activities of all published anomalies, our *Learning Ability (LA)* measure tends to be persistent by construction. In Figure 2, we further show the persistence of learning activities at the fund-publish month level. This helps rule out the methodological influence on the persistence of our measure and serves as evidence that learning ability is more related to managers' skill rather than luck. To be specific, we use $Binary\ L(t_f^j)$ to denote whether a fund *f* learns from a certain anomaly *j*. Then we define $Learn_{f,pt}$ as the maximum of $Binary\ L(t_f^j)$ among all anomalies published in month pt to represent whether fund *f* exhibits learning activity in publish month *pt.*[9] We use panel regressions of future $Learn_{f,pt+n}$ on $Learn_{f,pt}$ and a set of control variables:

$$Learn_{f,pt+n} = \alpha + \beta Learn_{f,pt} + \gamma Controls_{f,pt} + \varepsilon_{f,pt+n}. \qquad (4)$$

Control variables contain the fund characteristics in Table 2. The regressions include fund and publish month level fixed effects. The estimated regression coefficients on $Learn_{f,pt}$ and the 95% confidence intervals using different *n* are plotted in Figure 2.

[Figure 2 about here.]

As shown in Figure 2, the correlation of a fund's learning activity with its lagged value in the last publish month is highly significant at 7.2%. It indicates that if a fund learns from anomalies this time, then it will have a 7.2% higher probability to learn in the next publish month. This effect persists until the fourth month that contains anomaly publication(s) with coefficients at 4.5%, 5.2%, 5.9%, respectively. The coefficients turn insignificant after the fifth publish month, but are still positive till n=8. As a comparison, the average value of this dummy variable $Learn_{f,pt}$ at fund-publish month level is 66%. In summary, we find a rather long-term persistence in mutual funds' learning activities, which is both statistically and economically significant.

[9] It is important to note that the publish month (*pt*) only represents the time when at least one anomaly is published. Therefore, the publish month *pt+n* is not necessarily *n* successive calendar month after month *pt*; instead, it denotes the next *n*-th month that contains anomaly publication(s). To distinguish it from the quarterly time dimension, we use "*pt*" here.

4. Learning Ability and Fund Performance

4.1 Portfolio Evidence

In this section, we examine a strategy that predicts fund performance based on the fund's lagged *Learning Ability (LA*). We first conduct a portfolio approach. In each quarter end, we sort funds into five quintiles according to their *LA* measure. Within each quintile we calculate the equally average fund return realized in next month. In unreported results, we obtain qualitatively and quantitatively similar returns when funds in each decile are value-weighted (i.e., lagged TNA-weighted). We assess fund performance using representative performance adjustment models in the literature including fund gross returns, net returns (net of fee), CAPM alphas, Fama-French 3-factor alphas (Fama and French, 1993), Carhart 4-factor alphas (Carhart, 1997), and benchmark-adjusted Carhart 4-factor alphas.

[Table 4 about here.]

Table 4 reports the average fund future returns in each quintile as well as the performance difference between the funds with highest and lowest *LA*. Under most performance models, it is evident that fund performance increase monotonically in the ability to learn and trade according to anomaly publications. In the first column, the results indicate that the most responsive-to-anomaly-publication fund portfolio generates a gross return of 0.991% per month, while the least responsive fund portfolio generates a gross return of 0.863% per month. The difference in the gross return equals 0.127% per month (or 1.52% per annum), which is statistically significant at 5% level. The ranking and performance difference of *LA*-sorted quintiles for the returns after expenses (Net return) are very similar to the one before expenses. The magnitude of the performance difference increases further if we compare factor-adjusted returns between the top and the bottom quintiles, ranging from 0.129% to 0.156% per month. For example, in the fifth column, the highest *LA* funds outperform the lowest *LA* funds by an economically significant 0.156% per month (or 1.87% per annum) in Carhart 4-factor alphas, which is also statistically significant at 1% level.

Funds aim to create value for their investors through their skills in stock picking and market timing (e.g., Fama 1972, Daniel et al. 1997). We also utilize the holding-based DGTW model of Daniel et al. (1997) in Table 5 to examine the effect of *LA* on characteristic selectivity and characteristic timing. Mutual funds with highest *LA* tend to have higher selectivity measures (CS) than other funds. The difference in the CS measures between the top and the bottom quintiles equals 0.094% per month, which is statistically significant at 1% level. However, the difference in the cross-sectional fund returns becomes insignificant for the style-timing measures (CT). The evidence shows that funds that learn from anomaly publication exhibit better stock-picking abilities than the least responsive funds.

[Table 5 about here.]

In sum, we find evidence of unconditional cross-sectional variation in fund performance that is attributable to the fund's tendency to learn about and exploit newly-published trading opportunities. Next, we employ multivariate regressions that allow us to control for fund characteristics that might also influence fund performance.

4.2 Regression Evidence

We extend our analysis using multivariate regressions to further examine the *LA*-performance relation. Following the literature, we include the following set of lagged fund characteristics as control variables: the natural logarithm of TNA (Size), fund age in month (Age), fund expense ratio (Expense), fund turnover ratio (Turnover), past flow (Flow), past return (Past Return) and the natural logarithm of the number of stocks held by the fund (LnNstocks). We estimate the following Fama-MacBeth (1973) regression:

$$Performance_{f,q} = \alpha + \beta LA_{f,q-1} + \gamma Controls_{f,q-1} + \varepsilon_{f,q}, \tag{5}$$

where $Performance_{f,q}$ is the performance of fund *f* in quarter *q*, $LA_{f,q-1}$ is the *Learning Ability* measure of fund *f* in quarter *q-1*, $Controls_{f,q-1}$ is a vector of fund characteristics mentioned above. In the base results, we test all the performance measures used in the portfolio sorting analyses in Table 2.

As shown in Table 6, we find a strong and positive relation between *LA* and future fund performance across all specifications. A one-standard-deviation-higher *LA* significantly increases the annualized gross return by 0.18% points (0.146*0.003*4). Similarly, a one-standard-deviation-higher *LA* increases annualized Carhart4 alpha (net return, CAPM alpha, FF3 alpha, and benchmark-adjusted Carhart4 alpha) by 0.18% (0.23%, 0.23%, 0.12%, 0.12%) points. These results confirm the strong cross-sectional relation between fund's tendency to learn from anomaly publication and mutual fund performance.

[Table 6 about here.]

To ensure that *LA* measure is different from other managerial skill proxies documented in the literature, we examine whether other skill measures influence the predictability of LA y on future fund performance. We estimate the following Fama-MacBeth (1973) regressions:

$$Performance_{f,q} = \alpha + \beta LA_{f,q-1} + \delta Skills_{f,q-1} + \gamma Controls_{f,q-1} + \varepsilon_{f,q}, \quad (6)$$

where $Skills_{f,q-1}$ denotes other skill proxies including Ret Gap (Kacperzczyk, Sialm and Zheng, 2008), Industry Concentration Index (Kacperczyk et al. 2005), Active Share (Cremers and Petajisto 2009), and R-square (Amihud and Goyenko 2013). For brevity, we only demonstrate the regression results based on the Carhart 4-factor alphas. In the first four columns in Table 7, we contain our measure *LA* and add these skill proxies one by one. Then in the last column, we include all skill proxies and conduct a kitchen sink regression.

[Table 7 about here.]

It is evident that *LA* carries a positive and significant coefficient across all specifications. In addition, the magnitude of coefficients on *LA* is quite similar to that in Table 6. A one-standard-deviation-higher *LA* significantly increases annualized Carhart4 alpha by 0.12% to 0.18% points with different skill proxies included in the independent variables. Even when we include all skill proxies in the regression as shown in the last column, the *LA* -performance relation remains robust. This indicates that the predictability power of *LA* measure would not be absorbed by the existing skill proxies. At the same time, coefficients on other skill proxies in the first four columns are still significant with signals consistent with their original papers. This also reflects incremental information content of our measure compared with other skill proxies.

Additionally, the trading activities and predictability of skill proxies might also be influenced by macroeconomic conditions in different sub-periods (Kacperczyk et al., 2014). Also, Stambaugh et al. (2012) document that the stock-level relation between mispricing and future returns varies over time. So as a further investigation, we explore the time varying role of fund learning ability based on the following measures about market conditions: average anomaly returns, market sentiment, liquidity and recession indicated by Chicago Fed National Activity Index (CFNAI). We first divide our sample into two groups using the median level of each market condition proxy, then conduct the same Fama-MacBeth (1973) regressions as in Table 6. The estimated coefficients are reported in Table 8.

[Table 8 about here.]

The results in column (1) to (4) indicate that the predictive power of *Learning Ability (LA)* on future fund performance comes largely from periods with higher average anomaly return and market sentiment. In the periods with higher anomaly return (sentiment), a one-standard-deviation increase in *LA* is associated with a higher annualized Carhart4 alpha of 0.153*0.006*4=0.37% (0.164*0.005*4=0.33%), which is statistically significant at 1% level. While in the low anomaly return and low sentiment periods, the regression coefficients are considerably smaller and insignificant. It has been well-documented that anomaly is stronger following high levels of sentiment (e.g., Stambaugh et al. 2012). Hence, results under both measures might point to the influence of existing anomaly performance on the predictive power of fund learning ability. In addition, the coefficients on *LA* in the last fourth columns are similar across high and low market situations, indicating that the role of fund learning remains similar under different market liquidity and business activity.

5. Learning Ability and Fund Flows

Our findings demonstrate mutual funds' tendency to learn about and exploit newly-published trading opportunities, which positively predicts future fund performance. However, the searching, replicating and trading adjustment during the fund learning process all come up with costs. As a manager's compensation largely depends on assets under management, it is natural to expect that managerial abilities relate positively to asset growth by generating higher returns and attracting higher inflows. In this way, the managers could be motivated to learn from academia and trade following the anomalies to obtain better compensation despite of the costs of learning. In the previous section, we report the LA -performance relation. In this section, we further investigate how mutual fund investors react to mutual fund learning ability, as measured by the net fund flows in the next quarter. We estimate the following Fama-MacBeth (1973) regression:

$$Flow_{f,q} = \alpha + \beta LA_{f,q-1} + \delta Skills_{f,q-1} + \gamma Controls_{f,q-1} + \varepsilon_{f,q}, \qquad (7)$$

where $Flow_{f,q}$ is the normalized net flow into fund f over quarter q, $Skills_{f,q-1}$ denotes one or more skill measures, $Controls_{f,q-1}$ is a vector of control variables of fund characteristics including $Flow_{f,q-1}$ and $Past\ Return_{f,q-1}$ to control for the well-documented flow-performance relation (e.g., Chevalier and Ellison 1997).

[Table 9 about here.]

Table 9 presents the regression results. In the first four columns of the table, we contain our Learning Ability measure LA, all control variables and add these skill proxies one by one. Then in the last column, we include all skill proxies and conduct a kitchen sink regression. As expected, past fund flows and past returns are strong and positive predictors of the subsequent fund flows, confirming the effects of performance chasing in fund flows. A one-standard-deviation increase in past quarter fund flows and returns increase fund flows by 3.36% (0.094*0.357) and 2.61% (0.098*0.266) as shown in column (1) when including Return Gap measure. Moreover, we find a statistically significant yet negative relation between future flows and fund age as well as turnover, so older funds and actively trading funds are associated with lower flows.

Focusing on the predictive power of our core measure, *Learning Ability (LA)*, there is a positive relation between *LA* and fund flow, and this result is unaffected by controlling for various fund characteristics (including past fund flows and returns) and other skill proxies (including Retgap, ICI, Active Share and R2). A one-standard-deviation increase in *LA* is associated with a higher quarterly flow of 0.09% (0.146*0.006) as shown in column (1) when including Retgap measure, which is statistically significant at 5% level. Although the magnitude is considerably smaller than the effect of past fund flows and returns, as the mean quarterly flows is -1.1% and the mean TNA is around 1.6 billion dollars, the economic effect is still not neglectable. At the same time, this is not surprising because fund-level learning ability and anomaly trading strategies are not directly observable by investors.

The magnitude and significance of coefficients are similar under alternative specifications by considering other fund skill proxies. Overall, we employ multivariate regressions and document a strong positive predictive power of *LA* on future fund flows. Together with the learning-performance results in Section 3, we provide evidence that learning is helpful for enhancing manager's compensation, and thus rationale the action to learn from academia and exploit anomalies.

6. Conclusion

Anomaly strategies have been extensively studied, focusing on the selection of target anomalies and optimal trading timing. While these strategies can generate profits, the benefits are often constrained by the diffusion of information. In this ever-evolving market striving for profit opportunities, institutional investors, particularly mutual funds, are expected to lead in information capture. However, there is limited evidence to suggest that mutual funds engage in anomaly exploitation, regardless of the time frame analyzed — be it overall or in pre- and post-publication periods.

Building on this observation, we propose that variability exists in managerial capacity across the mutual fund industry. Some funds demonstrate a stronger capacity to assimilate and act upon newly published information, while others lag behind. By introducing the concept of *Learning Ability (LA)*, we measure a mutual fund's propensity to promptly adjust its anomaly-related positions following academic publications, thereby quantifying managerial skill in anomaly exploitation. Our analysis of 202 anomalies over the past four decades demonstrates that funds with higher *LA* significantly outperform those with lower *LA*, achieving an economically meaningful annual alpha of 2%.

Our findings underscore the importance of understanding how investors apply the anomaly strategies, which also influences the effectiveness of these anomalies in the market. Future research should explore intriguing questions, such as whether mutual fund managers are aware of anomalies before their publication and if the industry can indeed outpace academia in this regard. Identifying exceptional fund managers who effectively apply this knowledge would provide valuable insights into investment strategies and performance outcomes. Overall, our work highlights the critical need for a deeper understanding of the relationship between academic research and practical application in mutual fund management.

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Figure 1: The Transformation of T-value to Learning Ability Measure

The figure illustrates the relation between the t-value (horizontal axis) and the probability of learning, L(t) (vertical axis).

$$L(t) = Max(0, 2\Phi(t) - 1) = Max(0, 1 - 2\alpha(t))$$

L(t) ranges from 0 to 1, increasing with the t-value. It is equal to zero when $t \leq 0$, demonstrating that learning only occurs when the t-value is positive.

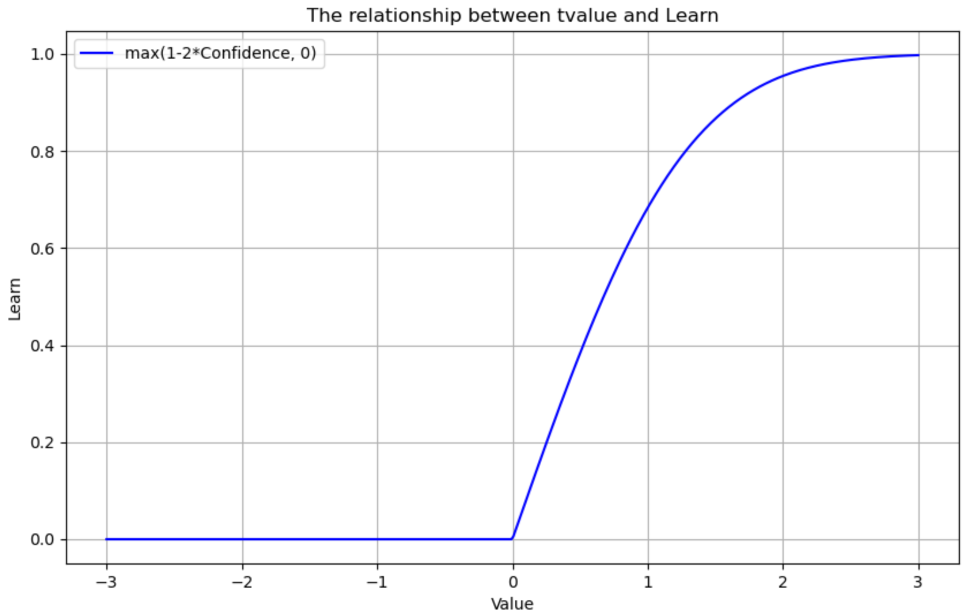


Figure 2: Persistence of Learning

The table presents the results of panel regressions examining the persistence of learning activities at the fund-publish month level.

$$Learn_{f,pt+n} = \alpha + \beta Learn_{f,pt} + \gamma Controls_{f,pt} + \varepsilon_{f,pt+n}$$

The dependent variable, $Learn_{f,pt+n}$ represents the learning activity of fund f in future publish month $pt+n$, while $Learn_{f,pt}$ captures whether fund f exhibited learning activity in publish month *pt*. Specifically, $Learn_{f,pt} = 1$ if fund *f* learns one of anomalies published in month *pt*, otherwise $Learn_{f,pt} = 1$; $Learn_{f,pt+n}$ if fund *f* learns one of anomalies published in month *pt+n*, otherwise $Learn_{f,pt+n} = 0$. We set n = 1 to 8. The estimated β and the 95% confidence intervals using different n are plotted in the figure.

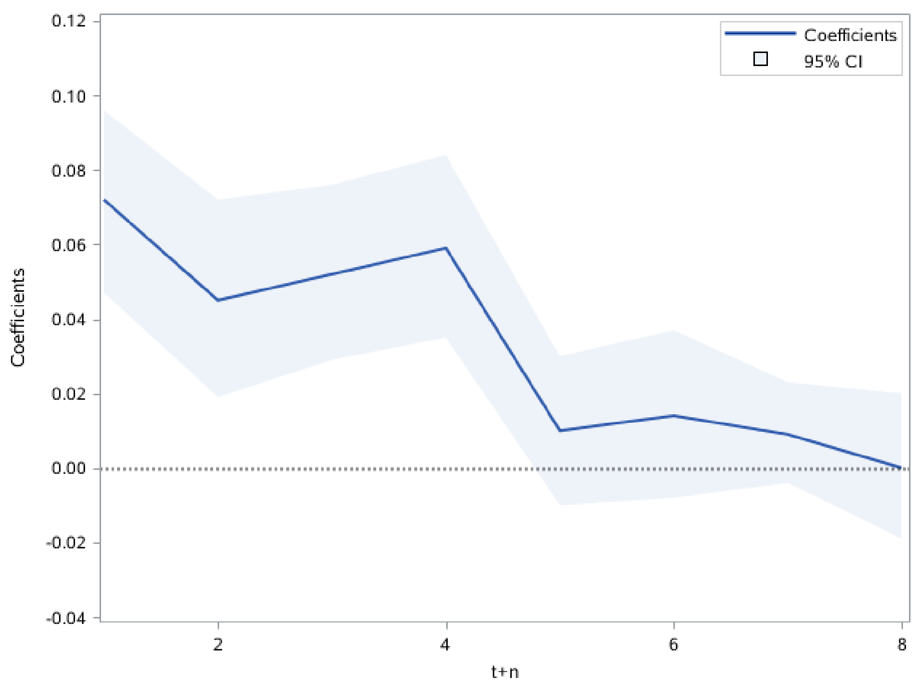


Table 1: Summary Statistics

This table reports the summary statistics for our main measure *Learning Ability (LA)*, fund characteristics and other skill proxies. The construction of *Learning Ability (LA)* is described in Section 2.1. Fund characteristics and other skill proxies are described in Appendix A. Panel A presents the mean, standard deviation, 25th percentile, median and 75th percentile of all variables at the fund-quarter level. Panel B presents the time-series average of cross-sectional correlation matrix. The sample period is from 1987Q4 to 2022Q4.

Panel A: Summary statistics

	N	Mean	St. Dev.	25th Pctl.	Median	75th Pctl.
Learning Ability (LA)	92245	0.482	0.146	0.406	0.476	0.551
TNA	92245	1596.762	4232.833	101.700	357.800	1231.868
Age	92245	213.614	135.664	112.000	179.000	277.000
Expense	92245	0.010	0.005	0.009	0.011	0.013
Turnover	92245	0.640	0.610	0.230	0.490	0.860
Flow	92245	-0.011	0.094	-0.045	-0.019	0.009
Past Return	92245	0.023	0.098	-0.020	0.032	0.078
Nstocks	92245	117.391	198.225	49.000	73.000	111.000
Retgap	91263	0.000	0.007	-0.003	0.000	0.003
ICI	91271	0.028	0.045	0.008	0.016	0.029
Active Share	91271	0.829	0.147	0.734	0.853	0.961
R2	91271	0.916	0.086	0.897	0.941	0.967

Panel B. Correlation matrix												
	Learning Ability (LA)	TNA	Age	Expense	Turnover	Flow	Past Return	Nstocks	Retgap	ICI	Active Share	R2
Learning Ability (LA)	1.000											
TNA	0.005	1.000										
Age	-0.040	0.275	1.000									
Expense	0.044	-0.184	-0.072	1.000								
Turnover	-0.027	-0.081	-0.013	0.294	1.000							
Flow	0.009	0.051	-0.013	-0.025	-0.042	1.000						
Past Return	0.013	0.021	0.006	-0.024	-0.011	0.112	1.000					
Nstocks	-0.008	0.170	-0.021	-0.137	0.001	0.034	0.020	1.000				
Retgap	-0.011	0.001	0.002	0.022	0.014	-0.014	0.082	0.008	1.000			
ICI	0.018	-0.053	-0.012	0.105	0.051	-0.034	0.004	-0.147	0.027	1.000		
Active Share	0.109	-0.226	-0.164	0.217	0.080	-0.007	0.004	-0.251	-0.001	0.201	1.000	
R2	-0.006	0.098	0.070	-0.197	-0.088	0.030	0.025	0.206	0.008	-0.507	-0.315	1.000

Table 2: Determinants of Learning Ability

This table presents the results of quarterly Fama-MacBeth (1973) regressions. All variable definitions are described in Appendix A. Note that the Anomaly Return* in this table exhibits heterogeneity across different funds, as we limited the selection of anomalies for each fund to those they have learned. Newey-West (1987) t statistics with a lag of 3 are reported in parentheses. *****, ******, and ******* represent significance levels of 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Dependent Variable: Learning Ability			
Size	0.001	0.003***	0.003***	0.004***	0.003***	0.002**	0.002**
	(1.530)	(3.980)	(4.130)	(5.060)	(4.550)	(2.430)	(2.380)
Age	-0.036***	-0.016***	-0.015**	-0.009*	-0.017***	-0.016**	-0.016**
	(-4.85)	(-2.69)	(-2.54)	(-1.68)	(-2.69)	(-2.51)	(-2.50)
Expense	0.377	1.393**	1.357**	1.321**	1.361**	1.304**	1.207**
	(0.640)	(2.130)	(2.100)	(2.280)	(2.050)	(2.420)	(2.270)
Turnover	-0.008***	-0.010***	-0.010***	-0.013***	-0.010***	-0.009**	-0.011***
	(-2.63)	(-3.32)	(-3.29)	(-4.60)	(-3.56)	(-2.51)	(-3.28)
Flow	0.009	0.013	0.021	0.006	0.019	-0.038	-0.030
	(0.480)	(0.660)	(1.050)	(0.310)	(0.990)	(-1.15)	(-0.92)
Past Return	-0.010	0.038	0.025	-0.042	0.036	0.032	0.031
	(-0.17)	(0.720)	(0.490)	(-0.88)	(0.750)	(0.550)	-0.570
LnNstocks	0.001	-0.005	-0.005	0.005*	-0.006	-0.006	-0.006
	(0.530)	(-1.22)	(-1.26)	-1.670	(-1.33)	(-1.46)	(-1.64)
Anomaly Return*	0.010***						
	(2.870)						
Retgap		-0.274*					
		(-1.95)					
ICI			-0.007				
			(-0.31)				
Active Share				0.183***			
				(3.930)			
R2					0.023		
					(0.830)		
Tenure						0.007***	
						(3.770)	
Team							0.002
							(0.970)
Constant	0.648***	0.528***	0.522***	0.299***	0.513***	0.502***	0.538***
	(13.41)	(13.58)	(13.76)	(5.63)	(11.57)	(13.02)	(12.85)
N. of Obs.	86598	89752	89760	89760	89760	78126	78126
N. of Qtrs.	140	140	140	140	140	140	140
R^2	0.113	0.069	0.067	0.100	0.069	0.077	0.073

Table 3: Learning across Anomaly Categories

This table reports the average learning tendencies of mutual funds across different types of anomalies. The second column shows the number of distinct types of anomalies within the sample. $\overline{L(t)}$ represents the average learning probability $L(t)$ at the fund-anomaly level. $\overline{Binary\ L(t)}$ provides the average value of Binary $L(t)$ at the fund level, where Binary $L(t)$ equals 1 if $L(t)$ is greater than 0, and 0 otherwise.

Anomaly Category	Total Number of Anomalies	Category Mean	
		$\overline{L(t)}$	$\overline{Binary\ L(t)}$
Trading	18	0.460	0.559
Analyst	12	0.443	0.592
Options	9	0.425	0.584
Accounting	105	0.407	0.526
Other	9	0.399	0.526
Price	42	0.394	0.530
13F	6	0.331	0.463
Event	1	0.312	0.500

Table 4: Mutual Fund Returns Sorted by Learning Ability

This table summarizes various performance measures for different portfolios of mutual funds. We assess fund performance using representative performance adjustment models in the literature including fund gross returns, net returns (net of fee), CAPM alphas, Fama-French 3-factor alphas (Fama and French, 1993), Carhart 4-factor alphas (Carhart, 1997), and benchmark-adjusted Carhart 4-factor alphas. The rows labeled "High-low" shows the differences in the abnormal returns between the top and bottom quintiles. Newey-West (1987) t statistics with a lag of 3 are reported in parentheses.

Rank of Learning Ability	**Gross return**	**Net return**	**Alpha CAPM**	**Alpha FF3**	**Alpha Carhart4**	**Bmk-adj.Alpha Carhart4**
Low	0.863***	0.788***	-0.103**	-0.102***	-0.120**	-0.033
	(3.63)	(3.31)	(-2.55)	(-2.74)	(-2.53)	(-0.74)
2	0.891***	0.820***	-0.020	-0.036	-0.029	0.058
	(4.20)	(3.86)	(-0.43)	(-0.91)	(-0.73)	(1.48)
3	0.901***	0.831***	-0.040	-0.027	-0.018	0.087**
	(4.00)	(3.69)	(-1.17)	(-0.89)	(-0.58)	(2.45)
4	0.936***	0.863***	-0.005	-0.001	-0.005	0.072**
	(4.17)	(3.84)	(-0.14)	(-0.03)	(-0.17)	(2.07)
High	0.991***	0.913***	0.038	0.044	0.036	0.096**
	(4.31)	(3.98)	(0.72)	(1.00)	(0.74)	(2.00)
High-low	**0.127****	**0.126****	**0.140*****	**0.146*****	**0.156*****	**0.129****
	(2.54)	**(2.52)**	**(2.71)**	**(3.00)**	**(2.84)**	**(2.48)**

Table 5: DGTW Decomposition

This table summarizes holding-based performance measures according to DGTW (1997) for different portfolios of mutual funds. The characteristic-based performance measures are denoted by CS (stock selection ability), CT (style-timing ability) and AS (style-selection ability). The rows labeled "High-low" shows the differences in the abnormal returns between the top and bottom quintiles. Newey-West (1987) t statistics with a lag of 3 are reported in parentheses.

Rank of Learning ability	**AS**	**CT**	**CS**
Low	0.828***	0.044*	0.050
	(4.01)	(1.78)	(0.96)
2	0.813***	0.059*	0.062
	(4.02)	(1.85)	(1.61)
3	0.810***	0.051	0.074*
	(3.81)	(1.53)	(1.86)
4	0.856***	0.038	0.065
	(4.14)	(1.59)	(1.59)
High	0.897***	0.028	0.144***
	(4.24)	(1.06)	(2.88)
High-low	**0.070***	**-0.016**	**0.094*****
	(1.91)	**(-0.78)**	**(2.58)**

Table 6: Learning Ability and Mutual Fund Performance: Regression Analysis

This table reports Fama-MacBeth (1973) regressions of fund future performance on the learning ability (LA) and other fund characteristics. The construction of learning ability is described in Section 2.1, and other fund characteristics are described in Appendix A. Newey-West (1987) t statistics with a lag of 3 are reported in parentheses. *****, ******, and ******* represent significance levels of 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Gross Return	**Net Return**	**Alpha CAPM**	**Alpha FF3**	**Alpha Carhart4**	**Bmk-adj.Alpha Carhart4**
Learning Ability	0.003*	0.004*	0.004**	0.002**	0.003***	0.002**
	(1.72)	(1.72)	(2.08)	(2.49)	(3.27)	(1.99)
Size	0.000	0.000	0.000	0.000	0.000	0.000
	(-0.36)	(-0.34)	(-0.75)	(0.21)	(0.51)	(-0.40)
Age	0.000	0.000	-0.001	-0.001*	-0.001*	-0.001
	(-0.85)	(-0.92)	(-1.00)	(-1.97)	(-1.91)	(-1.03)
Expense	0.113	-0.142*	0.060	0.118**	0.077	0.046
	(1.40)	(-1.75)	(0.81)	(2.15)	(1.22)	(0.64)
Turnover	-0.001	0.000	-0.001	0.000	0.000	-0.001
	(-0.54)	(-0.51)	(-0.62)	(0.21)	(-0.61)	(-1.13)
Flow	0.006	0.006	0.005	0.006	0.003	0.004
	(1.20)	(1.18)	(1.08)	(1.53)	(0.82)	(1.23)
Past Return	0.060*	0.060*	0.059*	0.029	0.013	0.007
	(1.97)	(1.97)	(1.85)	(1.44)	(0.76)	(0.43)
LnNstocks	0.00	0.00	0.00	0.001*	0.00	0.001**
	(0.96)	(0.96)	(0.68)	(1.95)	(1.15)	(2.07)
Constant	0.019**	0.019**	-0.003	-0.002	0.000	0.001
	(2.58)	(2.60)	(-0.71)	(-0.68)	(0.08)	(0.36)
N. of Obs.	92245	92245	92245	92245	92245	92245
N. of Quarters	141	141	141	141	141	141
R^2	0.2	0.2	0.184	0.112	0.102	0.09

Table 7: Learning Ability, Other Ability Measures and Fund Performance

This table reports Fama-MacBeth (1973) regressions of fund future performance (measured by Carhart4 Alpha) on the learning ability (LA) and other fund characteristics. The construction of learning ability is described in Section 2.1, and controls variables (other fund characteristics) and skill proxies are described in Appendix A. Newey-West (1987) t statistics with a lag of 3 are reported in parentheses. *, **, and *** represent significance levels of 10%, 5%, and 1%, respectively.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
	Dependent Variable: Fund Performance (Alpha Carhart4)				
Learning Ability	0.003***	0.003***	0.002**	0.003***	0.002*
	(3.42)	(3.10)	(2.30)	(3.15)	(1.96)
Retgap	0.070*				0.057
	(1.83)				(1.51)
ICI		0.024***			0.020**
		(3.67)			(2.49)
Active Share			0.008**		0.006
			(1.99)		(1.60)
R2				-0.013**	-0.004
				(-2.02)	(-0.47)
Constant	0.000	-0.004	-0.009*	0.008	-0.011
	(-0.02)	(-1.06)	(-1.87)	(1.57)	(-1.28)
Controls	Y	Y	Y	Y	Y
N. of Obs.	91263	91271	91271	91271	91263
N. of Quarters	140	140	140	140	140
R^2	0.110	0.119	0.121	0.123	0.163

Table 8: The Predictability of Learning under Different Market Conditions

This table reports Fama-MacBeth (1973) regressions of fund future performance (measured by Carhart4 Alpha) on the learning ability (LA) and other fund characteristics under different market conditions. The construction of learning ability is described in Section 2.1, and other fund characteristics and market condition proxies are described in Appendix A. Newey-West (1987) t statistics with a lag of 3 are reported in parentheses. *****, ******, and ******* represent significance levels of 10%, 5%, and 1%, respectively.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
	Dependent Variable: Fund Performance (Alpha Carhart4)							
	Anomaly Return		**Sentiment**		**Liquidity**		**CFNAI**	
	High	**Low**	**High**	**Low**	**High**	**Low**	**High**	**Low**
Learning Ability	0.006***	0.000	0.005***	0.001	0.004***	0.003*	0.003**	0.004**
	(4.09)	(-0.06)	(4.16)	(0.70)	(2.89)	(1.85)	(2.25)	(2.17)
Size	0.000	0.000	0.000	0.000*	0.000	0.000	0.000	0.000
	(-0.13)	(0.98)	(-0.87)	(1.87)	(-0.40)	(1.20)	(0.79)	(-0.02)
Age	-0.001**	-0.001	-0.001*	-0.001	-0.002*	-0.001	-0.002***	0.000
	(-2.45)	(-0.94)	(-1.75)	(-1.11)	(-1.81)	(-1.16)	(-3.09)	(-0.37)
Expense	0.026	0.135	0.021	0.144	0.062	0.092	0.095	0.057
	(0.34)	(1.45)	(0.27)	(1.64)	(0.73)	(1.13)	(1.28)	(0.60)
Turnover	-0.001	0.000	0.000	0.000	-0.002***	0.001	0.000	-0.001
	(-0.94)	(0.16)	(-0.57)	(-0.29)	(-3.37)	(1.38)	(0.16)	(-1.01)
Flow	0.002	0.003	0.005	0.000	0.004	0.002	0.008*	-0.003
	(0.41)	(0.77)	(0.95)	(0.09)	(0.71)	(0.36)	(1.72)	(-0.63)
Past Return	0.034	-0.010	0.033*	-0.012	0.051**	-0.023	0.022	0.002
	(1.64)	(-0.34)	(1.71)	(-0.41)	(2.04)	(-1.08)	(0.91)	(0.09)
LnNstocks	0.001**	-0.001	0.001	0.000	0.001*	0.000	0.000	0.001
	(2.11)	(-1.26)	(1.02)	(0.48)	(1.82)	(0.14)	(0.10)	(1.31)
Constant	0.000	0.001	0.004	-0.004	0.003	-0.002	0.009**	-0.009
	(0.01)	(0.15)	(0.81)	(-0.68)	(0.62)	(-0.46)	(2.05)	(-1.56)
N. of Obs.	45307	45964	45142	47103	45683	46562	44203	48042
N. of Quarters	77	63	77	64	69	72	74	67
R^2	0.106	0.098	0.098	0.106	0.109	0.094	0.106	0.097

Table 9: Learning Ability and Fund Flows

This table reports Fama-MacBeth (1973) regressions of fund future flow on the learning ability (LA) and other fund characteristics. The construction of learning ability is described in Section 2.1, and other fund characteristics are described in Appendix A. Newey-West (1987) t statistics with a lag of 3 are reported in parentheses. *, **, and *** represent significance levels of 10%, 5%, and 1%, respectively.

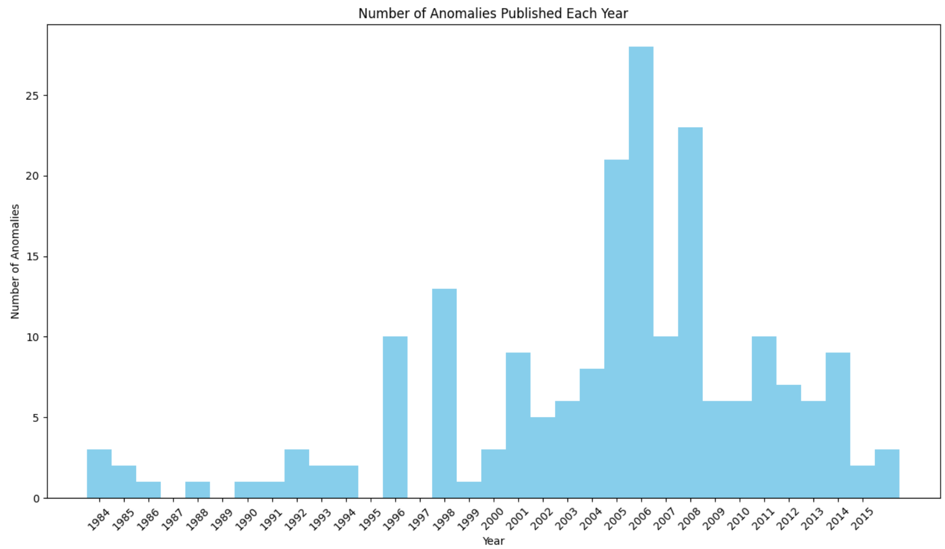
	(1)	(2)	(3)	(4)	(5)
	Dependent Variable: Fund Performance (Alpha Carhart4)				
Learning Ability	0.006**	0.006**	0.004*	0.005**	0.005*
	(2.53)	(2.39)	(1.73)	(2.12)	(1.94)
Size	0.000	0.000	0.000	0.000	0.000
	(0.10)	(0.23)	(0.21)	(0.06)	(0.20)
Age	-0.003**	-0.003***	-0.002*	-0.003**	-0.003**
	(-2.45)	(-2.85)	(-1.79)	(-2.47)	(-2.43)
Expense	0.007	0.077	0.001	0.048	0.028
	(0.05)	(0.56)	(0.01)	(0.34)	(0.20)
Turnover	-0.003***	-0.003***	-0.004***	-0.003***	-0.004***
	(-3.10)	(-3.04)	(-3.28)	(-2.98)	(-3.28)
Flow	0.357***	0.357***	0.354***	0.359***	0.358***
	(18.94)	(18.87)	(18.44)	(19.53)	(19.26)
Past Return	0.266***	0.274***	0.291***	0.269***	0.293***
	(10.42)	(11.04)	(11.02)	(10.19)	(10.51)
LnNstocks	-0.001	-0.001	0.000	-0.001	0.000
	(-0.88)	(-0.85)	(0.01)	(-0.72)	(-0.12)
Retgap	0.113*				0.098
	(1.94)				(1.64)
ICI		0.012			0.005
		(1.18)			(0.42)
Active Share			0.013*		0.013*
			(1.89)		(1.79)
R2				-0.011	-0.006
				(-1.39)	(-0.61)
Constant	0.002	0.003	-0.012	0.013	-0.003
	(0.28)	(0.39)	(-0.91)	(1.15)	(-0.21)
N. of Obs.	89752	89760	89760	89760	89752
N. of Quarters	140	140	140	140	140
R^2	0.204	0.207	0.206	0.206	0.221

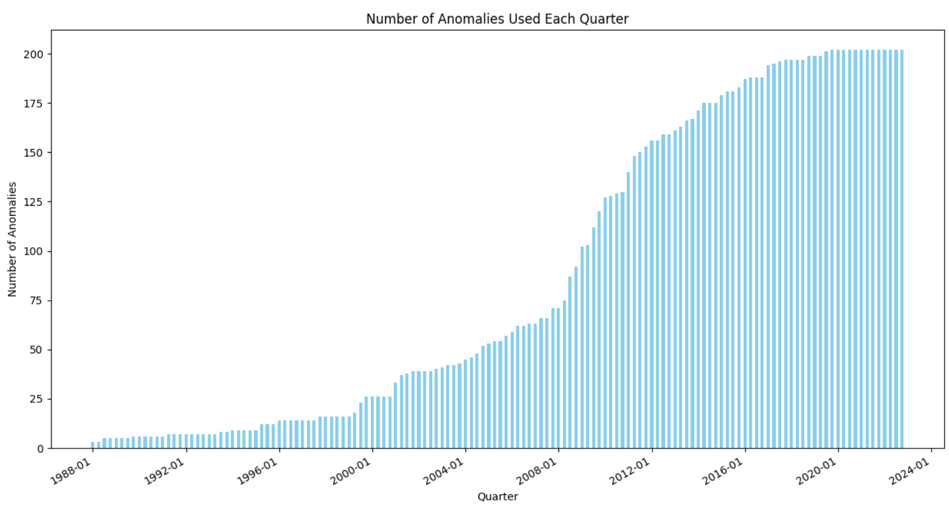
Appendix A: Variable Definitions

Variable Name	Variable Definition
A. Managerial skill measures	
Anomaly Investing Measure (AIM)	Anomaly Investing Measure for anomaly *j* in a given quarter *q* is computed as follows: $$AIM_{f,q}^{j}=\sum_{i}(w_{i,f,q}-w_{i,b,q})Decile_{i,q}^{j}$$ where $Decile_{i,q}^{j}$ is the decile rank of stock *i* based on anomaly *j* at the quarter-end *q*, $w_{i,f,q}$ and $w_{i,b,q}$ are portfolio weight of stock *i* in the fund *f* and in its index benchmark *b*.
Learning Ability (LA)	Learning Ability in a given quarter *q* is computed as follows: $$Learning\ Ability_{f,q}=\frac{1}{N_q}\sum_{j=1}^{N_q}L(t_f^j)$$ where $L(t_f^j)$ is the fund's probability of learning from the anomaly j, and N_q denote the number of anomalies used for calculation at the quarter-end *q*. The probability of learning is computed as follows: $$L(t)=Max(0,2\Phi(t)-1)$$ where $\Phi(t)$ is the standard normal cumulative distribution function and *t* refers to the t-statistics of the Post dummy in the time-series regression around publication.
Retgap	Return gap measures the difference between the reported fund return and the return on a portfolio that invests in the previously disclosed fund holdings (Kacperzczyk, Sialm and Zheng, 2008),
ICI	Industry concentration index measures the difference between the industry weights of a mutual fund and the industry weights of the total market portfolio (Kacperczyk, Sialm, and Zheng, 2005) and is computed as following: $$ICI_{f,q}=\sum_{j}^{10}(w_{j,f,q}-w_{j,m,q})^2$$ where $w_{j,f,t}$ and $w_{j,m,t}$ are the investment weight of industry j in fund f and in the market portfolio.
Active Share	Active Share measures the percentage of fund holdings that is different from the benchmark holdings (Cremers and Petajisto, 2009). The data can be downloaded from Martijn Cremers' website at http://activeshare.nd.edu. For any missing values, we adopt the authors' approach to compute and fill them.
R2	R2 measures the R square from a time-series regression of fund returns on market, size, value, and momentum factors over the previous 24 months (Amihud and Goyenko, 2013).
B. Fund performance	
Net Return	The monthly return reported by the CRSP survivorship bias-free mutual fund database.
Gross Return	Gross returns are calculated by adding the monthly expenses (annual expenses divided by 12) back to the net fund returns.
Alpha	Alpha is computed by subtracting the product of a fund's betas and the realized factor returns from the fund's returns for a given month. The suffixes namely CAPM, FF3, and Carhart4 refer to Jensen's (1968) one-factor alpha, Fama and French's (1993) three-factor alpha, and Carhart's (1997) four-factor alpha, respectively.

Bmk-adj. Alpha	Alpha computed using benchmark adjusted return.
C. Fund characteristics	
Size	The natural logarithm of total net assets (TNA) as of quarter-end, in millions.
Age	The natural logarithm of fund age, in months.
Expense	The ratio of total investment that shareholders pay for the fund's operating expenses, which include 12b-1 fees
Turnover	The minimum of aggregated sales or aggregated purchases of securities, divided by the average 12-month total net assets of the fund.
Past Return	The total return accumulated over the prior quarter.
LnNstocks	The natural logarithm of the number of stocks held by the fund.
Flow	The net flow into a fund over the prior quarter.
Tenure	The logarithmic average of the tenure of all managers overseeing the fund at the end of each quarter. This information is extracted from the Morningstar database.
Team	Equals 1 if more than one person manages the fund at the end of the quarter; and 0 otherwise. This information is extracted from the Morningstar database.
D. State variables	
Anomaly Return	Anomaly Return at month t is the average return of long-short strategies based on anomalies used to calculate *Learning Ability (LA)* at the end of the most recent quarter prior to month t.
Sentiment	Sentiment refers to the widely used Baker and Wurgler (2006) sentiment index, available for download at Jeffrey Wurgler's website (http://people.stern.nyu.edu/jwurgler/).
Liquidity	Liquidity refers to the level of aggregate liquidity from Pastor and Stambaugh (2003), available for download at Lubos Pastor's website (https://faculty.chicagobooth.edu/lubos-pastor/data)
CFNAI	The Chicago Fed National Activity Index (CFNAI) is a monthly index designed to gauge overall economic activity and related inflationary pressure), available for download at https://www.chicagofed.org/research/data/cfnai/current-data.

Appendix B: Number of Anomalies





Appendix C: List of Anomalies

Anomaly Name	Source	Anomaly Name	Source
EarningsSurprise	(Foster, Olsen and Shevlin, 1984)	AbnormalAccruals	(Xie, 2001)
AnalystRevision	(Hawkins, Chamberlin, Daniel, 1984)	DelBreadth	(Chen, Hong and Stein, 2002)
FirmAge	(Barry and Brown, 1984)	Illiquidity	(Amihud, 2002)
MRreversal	(De Bondt and Thaler, 1985)	ProbInformedTrading	(Easley, Hvidkjaer and O'Hara, 2002)
LRreversal	(De Bondt and Thaler, 1985)	ChInv	(Thomas and Zhang, 2002)
BidAskSpread	(Amihud and Mendelsohn, 1986)	ForecastDispersion	(Diether, Malloy and Scherbina, 2002)
Leverage	(Bhandari, 1988)	GrLTNOA	(Fairfield, Whisenant and Yohn, 2003)
STreversal	(Jegadeesh, 1990)	OrderBacklog	(Rajgopal, Shevlin, Venkatachalam, 2003)
AgeIPO	(Ritter, 1991)	ExclExp	(Doyle, Lundholm and Soliman, 2003)
AM	(Fama and French, 1992)	BetaLiquidityPS	(Pastor and Stambaugh, 2003)
BMdec	(Fama and French, 1992)	Governance	(Gompers, Ishii and Metrick, 2003)
BookLeverage	(Fama and French, 1992)	IdioVolAHT	(Ali, Hwang, and Trombley, 2003)
Mom12m	(Jegadeesh and Titman, 1993)	Tax	(Lev and Nissim, 2004)
Mom6m	(Jegadeesh and Titman, 1993)	High52	(George and Hwang, 2004)
CF	(Lakonishok, Shleifer, Vishny, 1994)	Investment	(Titman, Wei and Xie, 2004)
MeanRankRevGrowth	(Lakonishok, Shleifer, Vishny, 1994)	NOA	(Hirshleifer et al., 2004)
AnnouncementReturn	(Chan, Jegadeesh and Lakonishok, 1996)	ChangeInRecommendation	(Jegadeesh et al., 2004)
Accruals	(Sloan, 1996)	dNoa	(Hirshleifer, Hou, Teoh, Zhang, 2004)
fgr5yrLag	(La Porta, 1996)	EquityDuration	(Dechow, Sloan and Soliman, 2004)
VolumeTrend	(Haugen and Baker, 1996)	cfp	(Desai, Rajgopal, Venkatachalam, 2004)
VolMkt	(Haugen and Baker, 1996)	TotalAccruals	(Richardson et al., 2005)
VarCF	(Haugen and Baker, 1996)	PriceDelayRsq	(Hou and Moskowitz, 2005)
CapTurnover	(Haugen and Baker, 1996)	PriceDelaySlope	(Hou and Moskowitz, 2005)
SP	(Barbee, Mukherji and Raines, 1996)	DelSTI	(Richardson et al., 2005)
RoE	(Haugen and Baker, 1996)	ForecastDispersionLT	(Anderson, Ghysels, and Juergens, 2005)
REV6	(Chan, Jegadeesh and Lakonishok, 1996)	IO_ShortInterest	(Asquith Pathak and Ritter, 2005)
GrSaleToGrReceivables	(Abarbanell and Bushee, 1998)	betaCC	(Acharya and Pedersen, 2005)
ZScore	(Dichev, 1998)	RIO_MB	(Nagel, 2005)
ETR	(Abarbanell and Bushee, 1998)	PriceDelayTstat	(Hou and Moskowitz, 2005)
AnalystValue	(Frankel and Lee, 1998)	betaNet	(Acharya and Pedersen, 2005)
GrGMToGrSales	(Abarbanell and Bushee, 1998)	betaRC	(Acharya and Pedersen, 2005)
AOP	(Frankel and Lee, 1998)	betaCR	(Acharya and Pedersen, 2005)
PredictedFE	(Frankel and Lee, 1998)	betaRR	(Acharya and Pedersen, 2005)
GrSaleToGrOverhead	(Abarbanell and Bushee, 1998)	RIO_Volatility	(Nagel, 2005)
DivYield	(Naranjo, Nimalendran, Ryngaert, 1998)	DelCOA	(Richardson et al., 2005)
LaborforceEfficiency	(Abarbanell and Bushee, 1998)	DelCOL	(Richardson et al., 2005)
ChInvIA	(Abarbanell and Bushee, 1998)	DelEqu	(Richardson et al., 2005)
GrSaleToGrInv	(Abarbanell and Bushee, 1998)	DelFINL	(Richardson et al., 2005)
DolVol	(Brennan, Chordia, Subra, 1998)	RIO_Turnover	(Nagel, 2005)
IndMom	(Grinblatt and Moskowitz, 1999)	DelNetFin	(Richardson et al., 2005)
PS	(Piotroski, 2000)	Activism1	(Cremers and Nair, 2005)
Coskewness	(Harvey and Siddique, 2000)	XFIN	(Bradshaw, Richardson, Sloan, 2006)
MomVol	(Lee and Swaminathan, 2000)	zerotradeAlt12	(Liu, 2006)
VolSD	(Chordia, Subra, Anshuman, 2001)	FEPS	(Cen, Wei, and Zhang, 2006)
std_turn	(Chordia, Subra, Anshuman, 2001)	IdioVol3F	(Ang et al., 2006)
sfe	(Elgers, Lo and Pfeiffer, 2001)	CoskewACX	(Ang, Chen and Xing, 2006)
RD	(Chan, Lakonishok and Sougiannis, 2001)	OperProf	(Fama and French, 2006)
ShortInterest	(Dechow et al., 2001)	HerfAsset	(Hou and Robinson, 2006)
KZ	(Lamont, Polk and Saa-Requejo, 2001)	RevenueSurprise	(Jegadeesh and Livnat, 2006)
rd_sale	(Chan, Lakonishok and Sougiannis, 2001)	ShareIss5Y	(Daniel and Titman, 2006)
AdExp	(Chan, Lakonishok and Sougiannis, 2001)	FR	(Franzoni and Marin, 2006)

Anomaly Name	Source	Anomaly Name	Source
RealizedVol	(Ang et al., 2006)	ShareIss1Y	(Pontiff and Woodgate, 2008)
CompEquIss	(Daniel and Titman, 2006)	EarningsConsistency	(Alwathainani, 2009)
FirmAgeMom	(Zhang, 2006)	CashProd	(Chandrashekar and Rao, 2009)
grcapx	(Anderson and Garcia-Feijoo, 2006)	Frontier	(Nguyen and Swanson, 2009)
IntanBM	(Daniel and Titman, 2006)	CPVolSpread	(Bali and Hovakimian, 2009)
IntanCFP	(Daniel and Titman, 2006)	tang	(Hahn and Lee, 2009)
IntanEP	(Daniel and Titman, 2006)	RIVolSpread	(Bali and Hovakimian, 2009)
IntanSP	(Daniel and Titman, 2006)	skew1	(Xing, Zhang and Zhao, 2010)
HerfBE	(Hou and Robinson, 2006)	realestate	(Tuzel, 2010)
betaVIX	(Ang et al., 2006)	ChEQ	(Lockwood and Prombutr, 2010)
Herf	(Hou and Robinson, 2006)	iomom_supp	(Menzly and Ozbas, 2010)
grcapx3y	(Anderson and Garcia-Feijoo, 2006)	iomom_cust	(Menzly and Ozbas, 2010)
WW	(Whited and Wu, 2006)	roaq	(Balakrishnan, Bartov and Faurel, 2010)
zerotradeAlt1	(Liu, 2006)	RDS	(Landsman et al., 2011)
NetEquityFinance	(Bradshaw, Richardson, Sloan, 2006)	ResidualMomentum	(Blitz, Huij and Martens, 2011)
NetDebtFinance	(Bradshaw, Richardson, Sloan, 2006)	OPLeverage	(Novy-Marx, 2011)
DownsideBeta	(Ang, Chen and Xing, 2006)	PctAcc	(Hafzalla, Lundholm, Van Winkle, 2011)
zerotrade	(Liu, 2006)	EntMult	(Loughran and Wellman, 2011)
NetDebtPrice	(Penman, Richardson and Tuna, 2007)	ChTax	(Thomas and Zhang, 2011)
EarnSupBig	(Hou, 2007)	SmileSlope	(Yan, 2011)
BPEBM	(Penman, Richardson and Tuna, 2007)	EarningsForecastDisparity	(Da and Warachka, 2011)
EBM	(Penman, Richardson and Tuna, 2007)	MaxRet	(Bali, Cakici, and Whitelaw, 2011)
NetPayoutYield	(Boudoukh et al., 2007)	PctTotAcc	(Hafzalla, Lundholm, Van Winkle, 2011)
OrderBacklogChg	(Baik and Ahn, 2007)	OptionVolume1	(Johnson and So, 2012)
Mom6mJunk	(Avramov et al, 2007)	OptionVolume2	(Johnson and So, 2012)
PayoutYield	(Boudoukh et al., 2007)	retConglomerate	(Cohen and Lou, 2012)
roic	(Brown and Rowe, 2007)	Cash	(Palazzo, 2012)
IndRetBig	(Hou, 2007)	InvGrowth	(Belo and Lin, 2012)
ChNNCOA	(Soliman, 2008)	IntMom	(Novy-Marx, 2012)
ChAssetTurnover	(Soliman, 2008)	EarningsStreak	(Loh and Warachka, 2012)
FailureProbability	(Campbell, Hilscher and Szilagyi, 2008)	DelayAcct	(Callen, Khan and Lu, 2013)
ChPM	(Soliman, 2008)	DelayNonAcct	(Callen, Khan and Lu, 2013)
CustomerMomentum	(Cohen and Frazzini, 2008)	OrgCap	(Eisfeldt and Papanikolaou, 2013)
CompositeDebtIssuance	(Lyandres, Sun and Zhang, 2008)	RDAbility	(Cohen, Diether and Malloy, 2013)
AssetTurnover	(Soliman, 2008)	DelDRC	(Prakash and Sinha, 2013)
MomOffSeason11YrPlus	(Heston and Sadka, 2008)	GP	(Novy-Marx, 2013)
AssetGrowth	(Cooper, Gulen and Schill, 2008)	BetaTailRisk	(Kelly and Jiang, 2014)
ChNWC	(Soliman, 2008)	GrAdExp	(Lou, 2014)
RetNOA	(Soliman, 2008)	hire	(Bazdresch, Belo and Lin, 2014)
PM	(Soliman, 2008)	BetaBDLeverage	(Adrian, Etula and Muir, 2014)
MomSeason11YrPlus	(Heston and Sadka, 2008)	dVolCall	(An, Ang, Bali, Cakici, 2014)
MomSeason06YrPlus	(Heston and Sadka, 2008)	dVolPut	(An, Ang, Bali, Cakici, 2014)
MomOffSeason	(Heston and Sadka, 2008)	dCPVolSpread	(An, Ang, Bali, Cakici, 2014)
Mom12mOffSeason	(Heston and Sadka, 2008)	BrandInvest	(Belo, Lin and Vitorino, 2014)
MomSeason	(Heston and Sadka, 2008)	BetaFP	(Frazzini and Pedersen, 2014)
MomSeasonShort	(Heston and Sadka, 2008)	ReturnSkew	(Bali, Engle and Murray, 2015)
MomOffSeason16YrPlus	(Heston and Sadka, 2008)	ReturnSkew3F	(Bali, Engle and Murray, 2015)
MomSeason16YrPlus	(Heston and Sadka, 2008)	OperProfRD	(Ball et al., 2016)
InvestPPEInv	(Lyandres, Sun and Zhang, 2008)	CBOperProf	(Ball et al., 2016)
MomOffSeason06YrPlus	(Heston and Sadka, 2008)	TrendFactor	(Han, Zhou, Zhu, 2016)