Do the Actively Managed Mutual Funds Exploit the Stock Market Mispricing?

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ABSTRACT

Constructing a proxy for mispricing with the fifteen well-known stock market anomalies, we examine whether actively managed equity mutual funds exploit mispricing. We find that, in the aggregate, mutual funds over-weight the over-valued stocks and under-weight the under-valued stocks relative to passive benchmark. We show that this phenomenon is explained by investment constraints and agency issues of fund managers. In addition, we find that mutual funds with the highest weights in under-valued stocks outperform those with the highest weights in over-valued stocks by the annualized four-factor alpha of 2.99% (t-statistics of 2.56). Overall, our findings indicate that underperformance of mutual funds is related with adverse allocation to anomalies' implied mispricing.

Keywords: Mutual funds, managerial skill, anomalies, mispricing

JEL classification: G10, G11, G20, G23

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1. Introduction

The asset pricing literature has paid considerable attention to mutual fund performance. Starting with Jensen's (1968) pioneering study, most studies have documented that actively managed mutual funds underperform the market or their benchmarks, on average.[1] This well-documented underperformance raises one important question. Why do actively managed funds underperform? The well accepted answer to this question is that efficient equity markets make it difficult for mutual fund managers to add value net of fees.

We revisit this fundamental issue by taking a different tack. That is, we borrow from the recent stock market anomaly literature to explain the underperformance of mutual funds. Numerous studies have documented the existence of cross-sectional anomalies in expected equity returns.[2] Firm characteristics such as size, book-to-market, past returns, investment, and profitability are now well-known to predict a firm's subsequent returns. Given underperformance of mutual funds, our conjecture is that mutual funds, on average, hold stocks with characteristics predicting lower returns. Using the fifteen well-known pricing anomalies, we study whether this is the case.

In conducting our experiment, we have one important assumption. The existence of cross-sectional anomalies appear to violate the efficient market hypothesis as stocks with seemingly less risky generate higher future returns. These anomalies may reflect either mispricing or model misspecifications. The maintained assumption in our paper is that cross-sectional anomalies are at least in part due to mispricing effect in the equity market. Our assumption is supported by a recent paper by Stambaugh, Yu and Yuan (2012) which documents that a broad set of anomalies is related with mispricing. From the efficient market point of view, if mutual fund managers are sophisticated or skilled, they construct trading strategies to exploit cross-sectional mispricing. We refer to it as 'sophisticated trader hypothesis'. To test this hypothesis, we investigate whether actively managed mutual funds exploit the stock market mispricing. As mutual funds are typically constrained from engaging in short sales,[3] fund managers should invest in under-valued stocks and avoid over-valued stocks to exploit stock market mispricing.

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[1] See, for example, Sharpe (1966), Jensen (1968), Grinblatt and Titman (1989), Grinblatt and Titman (1993), Gruber (1996), Wermers (2000), Bollen and Busse (2001), Kacperczyk, Sialm and Zheng (2005), Avramov and Wermers (2006), Kosowski, Timmermann, Wermers and White (2006), Kacperczyk and Seru (2007), French (2008), Cremers and Petajisto (2009), and Busse, Goyal and Wahal (2014).

[2] For example, McLean and Pontiff (2014) examine the robustness of 82 anomalies variables after the initial publication. Green, Hand and Zhang (2013) identify more than 330 return predictive signals and use 60 in their tests. Hou, Xue and Zhang (2015) examine 80 anomalies. Jacobs (2015) explore 100 anomalies in the cross-section of expected equity returns.

[3] Chen, Desai and Krishnamurthy (2013) report that the proportion of mutual funds that actually use short sales in a given

A key element of our empirical work lies in constructing a proxy for mispricing. Mispricing is the difference between the observed price and the fundamental price under the absence of arbitrage. Unfortunately, since mispricing is not observable, we should construct a proxy for it. In this paper, we use cross-sectional anomalies as proxies for mispricing. Although individual anomaly itself could be served as a proxy for mispricing, we believe that each individual anomaly may be a noisy proxy for mispricing. To increase precision of proxy for mispricing, we attempt to diversify away some noise in each individual anomaly by aggregating information embedded in each measure of anomaly. To this end, for each stock, we combine the information associated with the fifteen well-known anomalies to construct anomalies' implied mispricing measure, and we define it as an A-score of a stock. In addition, A-score captures the fact that funds normally do not trade on single return predictability attributes. We find that our A-score captures the cross-sectional mispricing well in the stock market. That is, stocks with higher A-score are more likely under-valued, and stocks with low A-score are more likely over-valued.

To quantify how actively a fund trades on the anomalies' implied mispricing, we construct an investing measure of a fund in a way similar to the momentum investing measure of Grinblatt, Titman and Wermers (1995). Our investing measure is the value-weighted average of A-score decile ranks of individual stocks held by each mutual fund. A high value of investing measure indicates that the fund primarily holds under-valued stocks, which in turn implies that they aggressively pursue the anomalies' implied mispricing strategy.

Our empirical findings are summarized as follows. First, our empirical results reject the sophisticated trader hypothesis. We find that, in the aggregate, mutual funds hold stocks with adverse direction of the anomalies' implied mispricing. The average mutual fund over-weights the over-valued stocks and under-weights the under-valued stocks relative to the passive benchmark. For instance, the portfolio weights of the funds in the most under-valued decile is 5.10% lower than that of the S&P500 index (t= -2.53), and the portfolio weights of the funds in the most over-valued decile is 3.76% higher than that of the S&P500 index (t= 6.43). Especially, funds with the smallest investing measure extremely over-weight the over-valued stocks relative to the benchmark. Our finding suggests that the adverse allocation to anomalies' implied mispricing is one possible reason why on average mutual fund cannot beat the market given the anomalies' implied mispricing strategy generates superior risk-adjusted performance in the stock market.

Second, we find that funds which hold greater proportions of higher A-score stocks (under-valued stocks)

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year is 2% in 1994, and it is increased to 7% in 2009.

outperform funds which hold stocks of lower A-score (over-valued stocks). The performance difference after fees between funds with the highest investing measure and funds with the lowest investing measure is significantly positive: the annualized alpha is 2.12% (t = 2.38) with the three-factor model and 1.56% (t =1.75) with the four-factor model. Therefore, our investing measure has a forecasting power for future fund returns. The predictive power of investing measure remains in the presence of control variables including fund size, fund age, expense ratio, turnover ratios, prior risk-adjusted returns, and prior flows.

Third, since fund investing measure is an important determinant of future fund performance, we study more on fund investing measure. We find that funds that trade on mispricing are older, charge lower expense ratios, and have lower total risk than funds that trade against mispricing. Since high-expense funds may target naive investors who are not responsive to expenses as documented by Gil-Bazo and Ruiz-Verdu (2009), a negative relation between expense ratio and investing measure indicates that agency problems may play a role in explaining the opposite side portfolio composition to anomalies' implied mispricing. In addition, we find persistence in fund investing measure over time. The persistence in investing measure indicates existence of persistence in trading strategies, suggesting that funds deliberately tilt their portfolio towards either low or high A-score stocks.

Given our empirical findings, we raise one fundamental question. We find that funds that tilt their portfolios towards under-valued stocks earn higher risk-adjusted returns. Unfortunately, however, we have shown that, in the aggregate, mutual funds hold stocks with adverse direction of the stock market mispricing with strong persistence. Then, why do professional money managers tilt their portfolio toward over-priced stocks? This question can be answered with investment constraints of mutual funds and agency problem of managers. First, mutual funds may not exploit stock market mispricing due to their investment constraints or restrictions. Frazzini and Pedersen (2014) show that more constrained investors hold risker asset when there is investment constraint such as leverage and margin. We observe that over-priced stocks are associated with high market beta, and funds with low investing measure have greater investment constraints. Thus, mutual funds may hold over-priced stocks due to their investment constraints consistent with the model of Frazzini and Pedersen.

Second, agency problems may help explain the adverse allocating behavior of funds. Karceski (2002) develops an agency model which suggest that active fund managers tilt their portfolio toward high-beta stocks when fund managers' objective is maximizing their management fee. The observed pattern that over-priced stocks are associated with high market beta is again consistent with this agency model. We also observe that over-valued stocks typically have a favorable long-term history of past returns and hence may appear to be safer choice as far as managers' personal career risks are concerned. Thus, funds' adverse allocation to mispricing might be caused by ill-motivated trades of agency-prone fund managers.

Although the literature on stock market anomalies is huge, the literature does not explicitly examine mutual funds from this perspective. There are only a few studies that examine whether mutual fund managers trade on a specific market anomaly. Grinblatt, Titman and Wermers (1995) find evidence that mutual funds hold past winners and they generate abnormal performance before expenses and transaction costs. Ali, Chen, Yao and Yu (2008) examine the impact of accruals anomaly on performance. They find that mutual funds do not trade on the accruals anomaly even though it is profitable after costs and fees. Tice and Zhou (2011) show that mutual funds do not trade on fundamental trading strategy, suggested by Piotroski (2000). Ali, Chen, Yao and Yu (2014) find evidence that mutual funds trade on PEAD strategy, but they argue that it is not profitable due to competition among funds. Our study differs from these studies in two important ways. First, while such studies investigate single attributes strategy such as momentum or accruals, we combine the information associated with fifteen pricing anomalies and investigate more general question about whether mutual funds exploit stock market mispricing. Since funds normally do not trade on single return predictability attributes, our approach may be more appropriate for studying these issues. Second, unlike previous papers, we further investigate why professional money managers tilt their portfolio toward over-priced stocks.

Our paper is also related to works on the impact of institutional investors on the market anomalies. Edelen, Ince and Kadlec (2014), Akbas, Armstrong, Sorescu and Subrahmanyam (2015), and Chen (2014) document that mutual funds appear to exacerbate cross-sectional mispricing. Our empirical findings are consistent with these studies in different contexts. These studies examine the impact of aggregate fund flow or institutional ownership on stock level mispricing, whereas our paper focuses on the cross-section of funds using their equity holdings characteristics. We also suggest some alternative potential explanations why mutual funds do not exploit mispricing and exacerbate mispricing in the stock market.

We also contribute to the literature on the skill of active management. Fund performance can be predicted by our fund investing measure. Fund's skill measures such as active share, tracking error, and R-square are generally measured by the deviation of fund holdings from a benchmark portfolio. One limitation of these measures is that they cannot capture the direction of the deviation. On the other hand, our investing measure incorporates the direction of deviation using stock's mispricing. Thus, our investing measure is an alternative predictor for future fund returns.

The remainder of this article is organized as follows. Section 2 describes the data and confirms the presence of stock market anomalies. Section 3 documents the return predictability of anomalies' implied mispricing. Section 4 examines whether mutual funds trade on anomalies' implied mispricing or not. Section 5 investigates the relation between the anomalies' implied mispricing strategy and subsequent fund performance. Section 6 describes the characteristics of funds that aggressively trade on anomalies' implied mispricing strategy and investigate the persistence of the strategy. Section 7 suggests some potential explanations on why mutual funds do not exploit stock market mispricing. Finally, Section 8 summarizes and concludes the paper.

2. Mutual Fund and Stock Sample

2.1. Mutual fund Data

Our mutual fund sample consists of actively managed U.S. domestic equity funds. Mutual fund equity holdings are from the CDA/Spectrum mutual fund holdings database maintained by Thomson Financial. Mutual fund returns and characteristics come from the CRSP Survivorship Bias Free Mutual fund database. We combine the CRSP Survivorship Bias Free Mutual fund database with the Thomson Financial CDA/Spectrum database to obtain our mutual fund sample. These two datasets are combined using the Mutual Fund Links (MFLINKS) matching dataset originally constructed by Russ Wermers.

Thompson Financial compiled holdings is from mandatory SEC filings as well as voluntary disclosures by mutual funds. Mutual funds are required to report their equity holdings to the SEC either quarterly (before 1985 or after May 2004) or semiannually (between 1985 and May 2004), although many funds voluntarily file their holdings quarterly even when not required. From the Thomson Financial data, we select all funds with reported investment objective (Thompson IOC) of aggressive growth (2), growth (3), growth and income (4), unclassified (9), and missing. Passive index funds and funds with apparently misreported investment objectives are excluded from our sample.[4]

The Thompson Financial data are then combined with the CRSP data to obtain complete information on fund holdings and returns. Before merging these two datasets, we combine multiple share classes as a single fund in the CRSP data. They have separate identification codes in the CRSP data but are treated as a single fund in the Thompson Financial data, since different share classes have the same holdings compositions. We aggregate all the observations pertaining to different share classes into one observation. For the total net assets,

[4] We exclude passive index funds by deleting those whose name includes the word "index", "Ind", "Idx", "S&P", "DOW", "Market", "Russell", and "Wilshire".

we compute the sum of total net assets in each share class to obtain the total net assets in the fund. For the other quantitative attributes of fund such as return, expense ratio, and turnover, we compute the value-weighted average across the share classes, where the weights are the lagged TNAs of the individual share classes. For the qualitative variables including fund name, year of origination, and objectives, we obtain the data from the share class with the oldest fund.

To address incubation bias of Evans (2010), we exclude observations where the year for the observation is prior to the reported fund-starting year, and where the names of the funds are missing in CRSP. To reduce database errors, we exclude funds with the TNA less than $10 million, funds with fewer than 10 identified stock positions, and funds with the ratio of the CRSP TNA to the total market value of reported holdings less than 50 percent or more than 150 percent. 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 final matched database has 3,268 distinct U.S. active equity funds from the second quarter of 1982 to the second quarter of 2011. Table 1 reports the summary statistics for our mutual fund sample over the entire sample period as well as snapshots taken in a few representative years: 1982, 1985, 1990, 1995, 2000, 2005, and 2011.

< Insert Table 1 >

On average, the total net assets of sample funds is $926.60 million, with an annual return of 11.95 percent, an annual turnover ratio of 86.21 percent, and an annual expense ratio of 1.17 percent. The average fund age is 15.99 years. The average number of stocks held in a fund is 106, and the median is 68. The number of funds increases from 196 in 1982 to 1,594 in 2011.

2.2. Stock Data and Definition of Anomaly Characteristics

All stock characteristics except dispersion in analysts' forecasts are constructed using CRSP and COMPUSTAT datasets. Dispersion in analysts' forecasts is based on the data from Institutional Brokers Estimate System (I/B/E/S). The monthly returns and prices for common stocks (CRSP SHRCD of 10 or 11) traded on the NYSE, AMEX, and NASDAQ come from CRSP. We exclude financial firms (CRSP SICCD between 6000 and 6999), and stocks with prices below or equal to $5 at the end of the previous month. To avoid survivorship bias, we adjust monthly stock returns for stock delisting using the CRSP monthly delisting file following Shumway (1997). COMPUSTAT annual data in calendar year t are taken from reports with fiscal year ends in year t-1. We use a six months gap to allow for possible late submission of accounting statements. Thus, annual accounting variables are used from the end of June of year t through the end of May of year t + 1. All characteristics based on the COMPUSTAT annual data follow this rule. COMPUSTAT quarterly data come from the most recent quarterly earnings report and are used for the following three months or until the next report, whichever comes sooner. All characteristic variables are separately matched with the stock returns in the current month to compute portfolio returns. Daily and monthly risk-free rate RF, Fama and French (1993) factors MKTRF, SMB, HML, and the Carhart (1997) momentum factor UMD are obtained from Ken French's Web site.[5]

The fifteen considered characteristics are divided into six groups. The classical group consists of size (S), book-to-market (B/M), and momentum (MOM). These three characteristics underlie the Carhart (1997) four-factor model. Investment variables capture the firm's capital investment. This group consists of total asset growth (AG), abnormal capital investments (CI), and investments-to-assets ratio (I/A). Financing characteristics measure firm's stock issuance activity with net stock issues (NSI) and composite stock issuance (CSI). Two accounting anomalies capture the firm's earnings management and balance sheet manipulation with accruals (ACC) and net operating assets (NOA), respectively. Measures of firm's performance such as Return on assets (ROA) and standardized unexpected earnings (SUE) belong to profitability group. Idiosyncratic volatility (IVOL), Ohlson O-score (OSC), and dispersion in analysts' forecasts (DISP) are grouped together as they broadly quantify uncertainty about the firm. The detailed definition of each characteristics is provided in Appendix.

3. Stock Mispricing Measure

3.1. Measure of Anomalies' Implied Mispricing

The aim of this subsection is to develop a measure of anomalies' implied mispricing in an attempt to separate likely under-valued stocks from over-valued stocks. Although individual anomaly itself could be a proxy for mispricing, we believe that each individual anomaly may be a noise proxy for mispricing. To increase precision of proxy for mispricing, we attempt to diversify away some noise in each individual anomaly by aggregating information embedded in each measure of anomaly.

To this end, we modify binary score approach of Piotroski (2000) and Mohanram (2005) by constructing the ternary signal to the fifteen individual anomaly characteristics. Piotroski (2000) constructs a binary F-score to search for value firms on the basis of financial statements. Similarly, Mohanram (2005) constructs a binary

[5] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. We thank Kenneth French for making these data available.

G-score to differentiate high quality growth firms from low quality growth firms. The scoring approach of Piotroski (2000) and Mohanram (2005) is based on sum of nine (eight) binary fundamental signals, accordingly their score range from zero to nine (eight). On the other hand, our measure of anomalies' implied mispricing is constructed by sum of fifteen anomalies' implied ternary signals, where each signal has three possible score: long (+1), neutral (0), or short (-1).

In detail, for each stock j and anomaly characteristic k at the end of June of a year t, the signal $S_{k,j,t}$ is one if the stock's anomaly characteristic at the end of June of a year t is in the long-leg (highest-performing 30%). On the other side, the signal $S_{k,j,t}$ is minus one if the stock's anomaly characteristic at the end of June of a year t is in the short-leg (lowest-performing 30%). If the stock's anomaly characteristic is in the neutral-leg (mid-performing 40%) or missing at the end of June of a year t, the signal $S_{k,j,t}$ is zero. The maintained assumption implicit in the construction of this signal is that each of characteristics-based strategies has a mispricing effect. Thus, if the stock is likely under-valued (over-valued) based on each anomaly, the signal indicates the purchase (sale) of that stock. To capture the anomalies' implied mispricing, we construct a new instrument, namely, the A-score of stocks. The A-score of stock j at the end of June of a year t is defined as sum of above ternary signals:

$$A - score_{j,t} = \sum_{k=1}^{15} S_{k,j,t} \ , \tag{1}$$

where $$S_{k,j,t} = \begin{cases} 1, & if\ stock\ j\ belongs\ to\ the\ long\ leg\ based\ on\ k^{th}\ characteristic \\ 0, & if\ stock\ j\ belongs\ to\ the\ neutral\ leg\ based\ on\ k^{th}\ characteristic \\ -1, & if\ stock\ j\ belongs\ to\ the\ short\ leg\ based\ on\ k^{th}\ characteristic \end{cases} \tag{2}$$

Here, the indexes j and k indicate the stock and the anomalies considered, respectively. In other words, the A-score is defined as the number of under-valuation signals of the stock j minus the number of over-valuation signals of the stock j out of the fifteen anomaly characteristics. The A-score has an intuitive interpretation. Since the A-score is composition of the individual anomaly signals, by definition, the A-score ranges from the -15 to 15. Thus, the positive (high) A-score means that the stock is more likely under-valued, and the negative (low) A-score indicates that the stock is more likely over-valued. For example, if a stock's A-score is 6, it indicates that the stock is under-valued by at least six signals. Based on the definition of the A-score, we hypothesize that: (1) Stocks of high A-score (under-valued stocks) will exhibit superior future performance, on average. (2) Funds that have stocks with higher A-score (under-valued stocks) will exhibit superior-performance, on average, relative to funds that have stocks with lower A-score (over-valued stocks).

3.2. Average Returns of Anomalies' Implied Mispricing-based Portfolios

In this subsection, we investigate the cross-sectional relation between A-score and subsequent return for stocks in our sample universe. Altogether, there are 127,150 firm-year observations in the sample, covering the period 1982–2011. 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 the A-score. We ensure that the accounting data for construction of the A-score are publicly available when we form portfolios. That is, portfolios are formed in June of each year t, and buy-and-hold portfolio returns are calculated from July of year t to June of year t+1.

< Insert Table 2>

Table 2 presents the average returns and stock characteristics for the deciles formed based on the A-score. Panel A reveals that returns of the decile portfolios monotonically increase across the A-score. For example, the average annual return is 3.48% for the lowest A-score decile portfolio (P1), and monotonically increases to 20.01% for the highest A-score decile portfolio (P10). The return spread between P10 and P1 (P10 − P1) is significantly positive, 16.53% (t = 6.88). The three-factor alpha of the return spread between P10 and P1 is also significantly positive. This spread is larger than the spread of individual anomaly based strategy indicating that our A-score measure captures the cross sectional mispricing in the stock market well. The table further shows that the alpha of the bottom three A-score deciles (P1 to P3) is significantly negative, hence, we refer to these stocks as over-valued stocks. On the other side, the alpha of the top three A-score deciles (P8 to P10) is significantly positive, therefore, we refer to these stocks as under-valued stocks.

The analysis is repeated on a subset of stocks held by the mutual funds in Panel B. Specifically, at the end of June in each year, we include stocks held by at least one fund into our sample. We refer to this sample as "stocks held by mutual funds." From 1982 to 2011, there are 71,308 firm-year observations in this sample. The results for the mutual fund holdings analysis exhibit similar patterns. The average annual return is 6.79% for the lowest A-score decile (P1) and 19.94% for the highest A-score decile (P10). The return spread between P10 and P1 is 13.19% (t = 5.70). The three-factor alphas also exhibit similar patterns.

Table 2 also reports the average size, market beta, and return volatility for each stock decile. In general, the A-score of stocks is positively related to size, while the A-score is inversely related to market beta, return volatility and idiosyncratic volatility. The results imply that under-valued stocks are larger, and exhibit lower systematic risk, lower total risk and lower idiosyncratic risk. Finally, the results for the mutual fund holdings analysis exhibit similar patterns. Compared to the stocks in the Stock Universe, stocks held by mutual funds have larger market capitalization and lower return volatility, consistent with the findings of prior studies [e.g., Lakonishok, Shleifer and Vishny (1992); Del Guercio (1996); Gompers and Metrick (2001)].

Table 2 shows that the return appears to be asymmetric with a strong negative for the lowest A-score stocks which is not mirrored by a strong positive for the highest A-score stocks. Stocks with the lowest A-scores perform particularly poorly. This is consistent with the findings of prior studies documenting anomalous returns are originated from abnormal returns from the short leg (over-valued stocks). Several studies attribute this long-short asymmetry to the argument of Miller (1977) that differences of opinion with short-sale constraints can cause overpricing [see also Diether, Malloy and Scherbina (2002); Stambaugh, Yu and Yuan (2012)]. Thus, to take advantage of the anomalies' implied mispricing, it is also important to avoid over-valued stocks since most mutual funds are banned from short-selling.

In sum, our empirical evidence has an important implication for mutual funds. To exploit this stock market mispricing, mutual funds should take long positions in under-valued stocks. In the next section, we will examine whether this is indeed the case.

4. Do Mutual Fund Hold Stocks Based on Mispricing Measures?

4.1. Construction of Fund Investing Measure

Given the evidence on the anomalies' implied mispricing in the stock market, an investor may argue that mutual funds should aggressively hold likely under-valued stocks. Thus, in this section, we test whether mutual funds trade on anomalies' implied mispricing. If mutual funds exploit cross-sectional mispricing, we expect that they over-weight for under-valued stocks and under-weight for over-valued stocks compared to the benchmark; in contrast, if mutual funds trade opposite side of cross-sectional mispricing, we expect that mutual funds over-weight for over-valued stocks and under-weight for under-valued stocks compared to the benchmark. For this purpose, we construct a fund investing measure to quantify how actively a fund follows the anomalies' implied mispricing strategy. This measure is in the spirit of the momentum investing measure of Grinblatt, Titman and Wermers (1995), and Ali, Chen, Yao and Yu (2008) also compute the accruals investing measure using the same approach.

Specifically, at the end of June of each year, we sort all stocks into deciles based on the A-score. The A-score ranking is from 1 to 10, with decile 1 (10) representing stocks with over-valued (under-valued). Given the holdings of a fund, we calculate the weighted average of the A-score rankings of that fund. The fund investing measure is the weighted average of the A-score decile rank of stocks held by the fund:

$$Investing\ Measure_{i,t} = \sum_{j=1}^{N} w_{i,j,t} * Rank_{j,t} \tag{3}$$

where $Rank_{j,t}$ is the decile rank of stock j based on the A-score. *N* is the number of stocks in the Stock Universe that are held by the fund in June of year t. $w_{i,j,t}$ is the value of stock *j* owned by fund *i* as a percentage of total value of stocks the fund holds at the end of June of year *t*:

$$w_{i,j,t} = \frac{n_{i,j,t} p_{j,t}}{\sum_{j=1}^{N} n_{i,j,t} p_{j,t}} \tag{4}$$

where $n_{i,j,t}$ is the number of shares of stock *j* held by the fund, and $p_{j,t}$ is the market price of stock *j* at the end of June of year *t*. A high value of investing measure indicates that the fund tilt its holdings toward under-valued stocks.

This procedure can be applied to any portfolio. We first compare two portfolios: the fund sample in the aggregate, where we pool the equity holdings of all funds into one portfolio, and passive benchmark portfolios. We use the S&P500 index as benchmark because the S&P500 index has been the most widely used in the literature. For robustness check, we also use the CRSP total market index as another benchmark portfolio. These comparisons allow us to determine whether funds as a whole are more or less aggressive with respect to the anomalies' implied mispricing strategy. We also conduct comparison across funds, so in our second exercise we calculate the investing measure for an individual fund.

This approach can be extended to any characteristics ranking variable. We extend this procedure by applying it to fifteen individual anomalies, and calculate each characteristic score of portfolios. For example, the *BMSCORE* of a fund is the weighted average book-to-market decile rank of stocks held by the fund. To make the relation between characteristic score and the direction of mispricing consistent in all characteristics considered, the characteristic ranking is from 1 to 10 with decile 1 (10) representing stocks with lowest-performing 10% (highest-performing 10%) for the ranking variable. Thus, a high characteristic score indicates that funds tilt their equity holdings toward stocks in the long-leg of a given anomaly characteristic.

4.2. Do Mutual Funds Exploit the Stock Market Mispricing?

In this subsection, we present the empirical evidence for fund investing measure. We start with a comparison of the investment style between the aggregate fund industry and the benchmark. If mutual funds as a whole trade on the anomalies' implied mispricing, then the average investing measure of the funds would be higher than the benchmark.

< Insert Table 3 >

Panel A of Table 3 reports the average value of portfolio investing measure for the funds, S&P500 index, and CRSP market index. First, focusing on the individual characteristic score of funds and benchmarks, the result shows that the characteristic scores for ME, AG, CI, I/A, NS, CSI, ACC, NOA, and DISP for the funds are significantly higher than the S&P500 index or the CRSP market index. On the other hand, for B/M, MOM, SUE, and ROA, the funds has significantly lower characteristic score than benchmarks. For IVOL and OSC, the difference in scores depends on the choice of benchmark. IVOL and OSC score are lower than that of the S&P500 index, but higher than that of the CRSP market index. This results suggest that mutual funds trade on anomalies related to size, investment, financing, and accounting, on average. On the other hand, on average they do not invest in anomalies related to book-to-market, momentum, profitability and uncertainty about firm.

While each anomaly is itself a mispricing measure, each individual anomaly may be a noisy measure of the mispricing. Fortunately, our investing measure diversifies away some noise in each individual anomaly and thereby increases precision of mispricing. In addition, using the investing measure is also justified by the fact that funds normally do not trade on single return predictability attributes. We proceed to investigate the same comparison using the investing measure. Panel A of Table 3 shows that the average investing measure of the funds is 4.50, and the average investing measure for the CRSP index is 6.44. The mutual fund in the aggregate tends to hold over-valued stocks than those in the S&P500 index or the CRSP market index. The result suggests that mutual funds do not invest in the anomalies' implied mispricing, on average.

We further look at the distribution of the portfolio weight of each stock decile ranked by the A-score. The portfolio weight of an A-score decile is computed as the total value of the stocks in the decile held by funds divided by the total value of their equity holdings. Panel B of Table 3 and Figure 1 report the time-series means of these portfolio weights. For comparison, we also report the portfolio weights of the S&P500 index and the CRSP market index. Consistent with the results using the investing measure, we find that mutual funds tend to under-weight for under-valued stocks and over-weight for over-valued stocks compared to the benchmark. Relative to the S&P500 index, the funds significantly overweight stocks in the lowest three A-score deciles, and significantly underweight stocks in the highest two A-score deciles. For instance, the portfolio weights of the funds on stocks in the most under-valued decile (P10) is 5.10% lower, and the portfolio weights of the funds on stocks in the most over-valued decile (P1) is 3.76% higher than that of the S&P500 index.

< Insert Figure 1 >

Our evidence rejects the prediction of the sophisticated trader hypothesis that the funds should invest in under-valued stocks to exploit the mispricing. Our results suggest that mutual funds have adverse allocation effects in the stock market mispricing. In addition, this adverse allocation to anomalies' implied mispricing may be one reason why on average mutual fund do not generate significant profit, given the anomalies' implied strategy generates superior risk adjusted performance. Our empirical findings are also consistent with studies suggesting that mutual funds appear to exacerbate cross-sectional mispricing [e.g., Edelen, Ince and Kadlec (2014); Akbas, Armstrong, Sorescu and Subrahmanyam (2015)].

Although mutual funds on average do not trade on the anomalies' implied mispricing, it is possible that a subset of funds may do so. To see this, we compute its investing measure for each fund as described, and then we rank funds into deciles based on their investing measures each year. We consider the funds in the highest decile (D10 funds) as most actively following the anomalies' implied mispricing strategy.

< Insert Table 4 >

Table 4 and Figure 2 report the time-series means of portfolio weights in each A-score sorted stock deciles for investing measure sorted fund deciles. We find that the top two investing measure decile (D9 to D10) funds correctly allocate their portfolio regarding to anomalies' implied mispricing, in other words, they overweight under-valued stocks (P8 to P10) and underweight over-valued stocks (P1 to P3) relative to the those of CRSP market index. Especially, D10 funds are significantly overweight stocks in the highest three A-score deciles (P8 to P10), and significantly underweight stocks in the lowest three A-score deciles (P1 to P3). The results indicate that there exist a small group of the mutual funds that trade on the anomalies' implied mispricing. However, the large number of funds hold stocks with opposite side of the anomalies' implied mispricing. The bottom seven investing measure decile (D1 to D7) funds adversely allocate their portfolio regarding to anomalies' implied mispricing. Furthermore, D1 funds extremely overweight over-valued stocks (P1 to P3) relative to the CRSP market index. These results suggest that despite prevailing mispricing in the stock market, only a small number of managers actually exploit the mispricing.

< Insert Figure 2 >

5. Performance Analysis

Given the anomalies' implied strategy generates superior risk adjusted performance, we hypothesize that there are cross-sectional differences in fund performance: Funds which holds greater proportions of higher A-score stocks (under-valued stocks) will exhibit over-performance relative to funds which hold stocks of lower A-score (over-valued stocks). In other words, the higher funds' investing measure, the higher its average performance.

5.1. Fund Performance across Investing Measure Sorted Portfolio

In this subsection, we study fund performance across investing measures. We look at two measures of fund performance: fund returns after fee and fund returns before fee. At the end June in year t, we calculate the fund returns after fee and before fee from July of year t to June of year t+1 for each fund. To measure abnormal returns, we consider the Fama and French (1993) three-factor alpha and the Carhart (1997) four-factor alpha for each fund-year with monthly fund returns. They are based on the following models respectively:

$$R_t - RF_t = \alpha + \beta_1 MKTRF_t + \beta_2 SMB_t + \beta_3 HML_t + \varepsilon_t \tag{5}$$

$$R_t - RF_t = \alpha + \beta_1 MKTRF_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 UMD_t + \varepsilon_t \tag{6}$$

where R_t is the fund return. RF_t is the risk-free rate as proxied by the yield on Treasury bills with one-month maturity. $MKTRF_t$ 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. We require at least seven monthly returns each year to estimate these models. We then calculate the annualized alpha by multiplying the estimated coefficient α by 12.

In Table 5, we report average annual performance across investing measure sorted fund decile. Each June of year t, we sort funds into investing measure deciles. We compute the equal-weighted performance within each of the ten fund portfolios over the entire sample period.

< Insert Table 5 >

For the full sample, the annualized three-factor alpha and the annualized four-factor alpha before fees are 0.07 and 0.03%, respectively. The corresponding values are −1.08 and −1.10% after fees. Our results on the profitability are consistent with prior studies which document that fund managers' superior stock selection ability may be able to generate higher returns than benchmark before fees, yet after fees investors' return may be below the benchmark [e.g., Berk and Green (2004); Carhart (1997); Wermers (2000)].

Table 5 suggests that the highest investing measure funds exhibit economically significant stock-picking ability: For D10 funds, the annualized before-fees three-factor and four-factor alphas are 0.97% (t = 2.07) and 0.87% (t = 1.83), respectively. In addition, we compare the performance of D10 funds with that of D1 funds. The result shows that the investing measure does improve fund performance. For the two risk adjusted performance measures— three-factor alpha, and four-factor alpha—the difference between the highest and lowest investing measure deciles is significantly positive: 1.97% (t = 2.14), and 1.55% (t = 1.81), respectively.

Table 5 also report the corresponding results for fund performances after fee. The high investing measure funds again outperform the low investing measure funds. The difference between the D10 and D1 deciles is significantly positive: 2.12% (t = 2.38) with the three-factor model and 1.56% (t =1.75) with the four-factor model. The risk-adjusted returns indicate that the highest investing measure funds essentially match their benchmark returns while the lowest investing measure funds lose to their benchmarks by 2.23% per year (t = -3.08), and the loss further remains to 1.77% (t = 2.44) under the four-factor model. The evidence indicates that the funds with low investing measure do worst in terms of net return destroying value for fund investors.

Table 5 further shows that both Sharpe ratios demonstrate a fairly monotonic positive relationship with mutual fund investing measure. Gross Sharpe ratio increases from 0.42 to 0.58, and net Sharpe ratio increases from 0.36 to 0.51. The difference in returns between the top and bottom decile is quite small. However, volatility drops steeply with investing measure deciles, suggesting that the increase in Sharpe ratio is mostly driven by the decline in volatility. The findings indicate that slanting their portfolio towards under-valued stocks can help mutual funds improve their mean-variance efficiency by increasing their Sharpe ratio and lowering their total risk.

5.2. Regression Analysis

To see whether the investing measure is an important determinant of fund performance in the presence of famous fund characteristics, we run pooled panel regressions of fund performance on fund characteristics:

$$\begin{aligned} alpha_{i,t} = {} & \beta_1 InvestingMeasure_{i,t-1} + \beta_2 \, log(TNA)_{i,t-1} + \beta_3 [log(TNA)]^2_{i,t-1} + \beta_4 \, log(AGE+1)_{i,t-1} \\ & + \beta_5 Expenses_{i,t-1} + \beta_6 Turnover_{i,t-1} + \beta_7 alpha_{i,t-1} + \beta_8 flow_{i,t-1} + YearDmmies + \varepsilon_{i,t} \qquad (7) \end{aligned}$$

The list of explanatory variables includes investing measure, fund size measured by the logarithm of fund total net assets, fund age, expense ratio, turnover ratios measured by the minimum of aggregated sales or aggregated purchases of securities divided by the average twelve-month TNA of the fund, prior risk-adjusted returns, and prior flows. We also control other predictors of future fund performance known from the literature, such as active share, tracking error, and R-square. Cremers and Petajisto (2009) show that active share,[6] a fraction of the fund's portfolio deviated from the benchmark index, is a proxy for stock selection. They find that funds with high active share outperform funds with low active share. Cremers and Petajisto (2009) also employ tracking error, volatility of the difference between a fund's portfolio return and its benchmark index return, as a proxy for active management. They suggest that funds with tracking error exhibit some skill. In addition, Amihud and Goyenko (2013) show that R-square, obtained from a regression of fund's return on a multifactor benchmark model, is measure of selectivity. They find that lower R-square implies greater stock selection skill. We estimate

[6] http://www.petajisto.net/data.html. We thank Antti Petajisto for making the active share data available.

above equation with robust estimators of variance clustered at fund level.

< Insert Table 6 >

Table 6 shows the estimation results for the panel regression which controls for mutual fund characteristics and other predictors. When the control variables are not included in the regression, the coefficient on investing measure is significantly positive for all versions of alphas (three-factor, and four-factor models) calculated with gross and net fund returns. When an investing measure of a fund is increased by one unit, its abnormal gross and net returns measured by the three-factor model will rise annually by 0.17% (t=2.64), and 0.23% (t=3.58) over the following year, respectively. Rather than being subsumed by other variables, the predictive power of investing measure actually remains when other variables are added. For example, one unit increase of investing measure rises annualized net four-factor alphas by 0.54% (t=5.27), after controlling for fund characteristics and other active skill measures. Thus, the information contained in our investing measure is different from that contained in other skill measures. Overall, our empirical results indicate that mutual funds that tend to hold under-valued stocks have higher risk-adjusted performance.

Altogether, the results in Tables 6 demonstrate predictability of the fund investing measure for fund performance. Funds' risk-adjusted performance is higher for funds with greater investing measure. This means that mutual funds that slant their portfolios towards under-valued stocks earn higher risk-adjusted returns, even after considering transaction costs and management fees.

6. Further Analysis on Fund Investing Measure

In the previous section, we have shown that fund investing measure is an important determinant of future fund performance. Therefore, we study more on fund investing measure in this section. Specifically, we examine determinants of fund investing measure and the persistence of fund investing measure.

6.1. Determinant of Fund Investing Measure

We perform a cross-sectional analysis of fund characteristics across investing measure. Panel A of Table 7 reports the average fund characteristics of each investing measure-sorted fund decile. We compare several characteristics of mutual funds across investing measure deciles: total net assets, expense ratio, turnover ratio, fund age, flow, the number of stocks held by a fund, market beta of funds, cash holdings of funds and other skill measures. All characteristics are measured at the end of June of each year t, the same time when fund investing measure is calculated. To see the relation between investing measure and other fund characteristics, we also run pooled panel regressions of fund investing measure on fund characteristics. Panel B of Table 7 reports the estimation results.

$$InvestingMeasure_{i,t} = \beta_1 \, log(TNA)_{i,t} + \beta_2 [log(TNA)]_{i,t}^2 + \beta_3 \, log(AGE+1)_{i,t} + \beta_4 Expenses_{i,t} + \beta_5 Turnover_{i,t} + \beta_6 flow_{i,t} + \beta_7 past\ performance_{i,t} + \beta_8 Volatiltiy_{i,t} + YearDmmies + \varepsilon_{i,t} \quad (8)$$

< Insert Table 7 >

Several patterns are worth mentioning. First, TNA and the number of stocks held by a fund exhibit inverted-U shaped pattern, which indicates that D10 funds have similar size and level of diversification to those of D1 funds. Smaller funds are able to pursue more active trading strategy because their trading causes less price impact than larger funds [e.g., Pástor, Stambaugh and Taylor (2015)]. Cremers and Petajisto (2009) also suggest that smaller funds are likely to deviate from their benchmark portfolio. Since both D1 and D10 funds deviate far from their benchmark by definition of investing measure, this result is consistent with existing studies.

Second, funds that allocate adversely to mispricing are charge higher expense ratios than funds trade on mispricing. Funds in the lowest investing measure decile are characterized by higher expense ratios –specifically, the mean expense ratio for decile 1 (decile 10) is 1.29% (1.08%). Gil-Bazo and Ruiz-Verdu (2009) find that high-expense funds do not outperform low-expense funds, even before subtracting expenses. They interpret this evidence as an agency problem in which high-expense funds target naive investors who are not responsive to expenses. The fact that the expense ratio is negatively related to the investing measure indicate that agency problems may play a role in explaining the opposite side portfolio composition to anomalies' implied mispricing. Adverse allocation of funds in D1 might be caused by ill-motivated trades of agency-prone fund managers.

Third, funds with lower investing measure are younger than funds with higher investing measure, on average. The positive relation between fund age and investing measure indicate that older funds are skilled and trade to take advantage of their stock selection, which in turn enhances their performance and contributes to their longevity.

Finally, Panel A of Table 7 shows that if we refer to prior studies, lowest investing measure funds (D1) exhibit high managerial skill. Funds that tilt their portfolio towards over-priced stock have the highest active share, highest tracking error, and lowest R-square. However, unlike previous studies, we fail to find that funds with high active share, high tracking error, and low R-square have superior returns. One possible reason is that our investing measure is not linearly related to other skill measures as shown in Panel B in Table 7. Thus, the information contained in our investing measure is different from that contained in other measures. One limitation of aforementioned skill measures is that they are calculated only based on the ground that how much the managed portfolio deviates from their benchmark. These measures cannot capture the direction of deviation.

On the other hand, our investing measure incorporates the direction of deviation using stock's mispricing. Thus, it is likely that D1 funds are extremely deviated from their benchmark by inferior money managers.

In sum, funds that trade on mispricing are older, charge lower expense ratios, and have lower total risk than funds that trade against mispricing.

6.2. Persistence of Fund Investing Measure

It is possible that a fund may have a high investing measure due to luck instead of deliberate trading. If a money manager deliberately maintains their portfolio towards under-valued stocks, we observe persistence in fund investing measure over time. For this purpose, we calculate the transition probabilities for D1 and D10 funds over the subsequent five years, and Table 8 reports the results.

< Insert Table 8 >

We find that funds with D1 and D10 are highly persistent both at short and long horizons. Funds in extreme deciles are more likely to stay in the same extreme deciles than to move to the middle or other extreme decile. After one year, 55.9% and 54.5% of D10 and D1 funds remain in the same decile, respectively. This tendency remains in longer horizons. More than one-third of funds in deciles one and ten remain in these deciles even after five years. The persistence in investing measure indicates existence of persistence in trading strategies, suggesting that funds deliberately tilt their portfolio towards either low or high A-score stocks.

7. Potential Explanations

We find that funds that tilt their portfolios towards under-valued stocks earn higher risk-adjusted returns. Unfortunately, however, we have shown that, in the aggregate, mutual funds hold stocks with adverse direction of the stock market mispricing with strong persistence. These two findings raise one fundamental question. Why do professional money managers tilt their portfolio toward over-priced stocks? By reviewing related literature, we propose some possible explanations for our empirical findings in this section.

First, it is possible that mutual funds cannot exploit stock market mispricing due to their investment constraints or restrictions. Mutual funds are usually prohibited from borrowing to finance the portfolio. Building a theoretical model, Frazzini and Pedersen (2014) show that when there are investment constraints such as leverage and margin, more constrained agent holds assets with higher beta, which results in low alpha. Our empirical finding is explained by the model. We show that over-priced stocks have high market beta and market beta monotonically decreases with A-score of stocks (See, Table 2). Since mutual funds are typically constrained to using leverage[7], consistent with Frazzini and Pedersen (2014), fund manager may hold over-priced stocks.

Further, we investigate whether that our investing measure is related with fund's level of investment constraints. Although we do not have direct measures for the level of investment constraints, we believe that two proxies partially capture the level of investment constraints. First, we use the market beta of fund as a proxy for the fund's constraints. Alankar, Blaustein and Scholes (2013) suggest that mutual funds tend to hold risker assets when leverage constraints bind, and Boguth and Simutin (2015) argue that market beta of mutual funds captures the leverage constraints. For example, consider a manager who wants to achieve a fund beta of 1.2. The manager can do this by borrowing 20% of the capital and investing everything in the market portfolio. However, constrained managers who are unable to borrow would invest in high-beta stocks. They can achieve a fund beta of 1.2 by holding stocks with this desired beta. Thus, we conjecture that funds with higher market beta are more constrained. Second, we use the fund's cash holdings as a proxy for the fund's constraints. Chordia (1996) and Yan (2006) suggest that fund's cash holdings are proxy for their shareholder's redemption need. When there is more uncertainty about redemptions, the fund holds more cash and this might be one investment constraint. Thus, we conjecture that funds with higher cash holdings are more constrained. Using these two proxies for investment constraints, our testable hypothesis as follow:

H: All else being equal, lower investing measure funds have higher investment constraints.

To this end, we estimate a pooled regression of investment constraints using our investing measure and other control variables. Specifically, we estimate the following regression:

$$Investment\ Constraints_{i,t} = \beta_1 InvestingMeasure_{i,t} + Controls + YearDmmies + \varepsilon_{i,t} \quad (9)$$

< Insert Table 9 >

Table 9 shows that funds with low investing measure are associated with high market beta and high cash holdings. For our pooled regression estimates, we find that the coefficient for the investing measure is negative and statistically significant. One unit decreases in investing measure results in 0.26% increases in cash holdings, and 0.02 increases in fund beta, after controlling various fund characteristics and other skill measures. Our results provide a robust finding that low investing measure funds have higher investment constraints.

[7] Almazan, Brown, Carlson and Chapman (2004) report that the proportion of mutual funds that actually were not permitted to engage in the borrowing is 22.4%, and in the margin is 91.1% during 1994 to 2000. They also report that the actual use of borrowing by funds that are permitted to engage in borrowing is 9.7%, and the actual use of margin is just 2.7%.

In sum, the fact that many funds deliberately tilt their portfolio towards over-priced stocks is potentially explained by the investment constraints of funds. We show that low investing measure funds have higher investment constraints. Due to the high constraints, they may tilt to over-priced stocks, characterized by high beta, consistent with model of Frazzini and Pedersen (2014).

Second, agency problems may help explain the adverse allocating behavior of funds. Karceski (2002) develops an agency model in which active fund managers tilt their portfolio toward high-beta stocks. Fund managers select stocks to maximize their fund's expected assets under management because they are compensated by management fee, which is proportional to the assets under management. Mutual fund investors chase return through time, in particular, there are large aggregate inflows into mutual funds after the market run-ups (Warther, 1995). Mutual fund investors also chase return across funds, so highest performing funds obtain the largest inflows (Sirri and Tufano, 1998). The interaction of these two flow-performance relationships induces that fund managers hold stocks which outperform during bull market to maximize their management fee. Since high-beta stocks tend to outperform in up markets, active fund managers tilt their portfolio toward high-beta stocks. Because over-priced (low A-score) stocks have high market beta, the fact that many funds tilt their portfolio towards over-priced stocks is potentially explained by this agency model of fund managers. To apply above argument, we investigate whether that our investing measure is related with agency costs of funds. Here, our testable hypothesis as follow:

H: All else being equal, lower investing measure funds have higher agency costs.

Unfortunately, we do not have direct observable measures for the agency costs. So, we examine three proxies of agency costs within a mutual funds. The first measure of agency costs is the fees that a fund charges its investors. Higher fees benefit the fund manager, but destroy value of the fund investors. This suggests that fees play a role in the agency conflict that exist between the fund manager and fund investors. Existing studies such as Gil-Bazo and Ruiz-Verdu (2009), and Ferris and Yan (2009) also suggest that fund fees capture agency costs of funds. Our second measure of agency costs is return gaps. Kacperczyk, Sialm and Zheng (2008) show that return gaps, the difference between the reported fund return and the return on a portfolio that invests in the previously disclosed fund holdings, captures unobserved actions on funds. One component of the unobserved actions is agency costs. They suggest that the fund's opaqueness might proxy for agency problems, and opaque funds tend to exhibit large return gaps. So, we use return gaps as a proxy for agency costs that the large return gaps is indicator for high agency costs. Our final measure of agency costs is fund size. Our use of fund size to capture agency costs is consistent with the use of firm value as a measure of agency costs in the corporate finance literature. Thus, the large fund size are proxy for high agency costs.

To examine whether that our investing measure is related with agency costs of funds, we estimate a pooled regression of agency costs using our investing measure and other control variables.

$$Agency\ Costs_{i,t} = \beta_1 InvestingMeasure_{i,t} + Controls + YearDmmies + \varepsilon_{i,t} \quad (10)$$

< Insert Table 10 >

For our pooled regression estimates, we find that the coefficient for the investing measure is negative and statistically significant for all three proxies of agency costs. Table 10 shows that funds with low investing measure exhibit high expense ratios, high return gaps, and large fund sizes. One unit decreases in investing measure results in 0.01% increases in expense ratio, 0.54% increases in return gap, and 0.22 increases in logarithm of fund size after controlling various fund characteristics and other skill measures. Our results provide a robust finding that low investing measure funds have higher agency costs.

Overall, our empirical findings from previous sections might be caused by ill-motivated trades of agency-prone fund managers. Due to the agency problem, they may tilt to over-priced stocks, characterized by high beta, consistent with model of Karceski (2002).

We also conjecture that over-valued stocks typically have a favorable history of past returns and hence may appear to be safer choice as far as managers' personal career risks are concerned.

< Insert Figure 3 >

Panel A of Figure 3 displays average long-term past cumulative returns of each A-score stock decile, and Panel B shows past 60-months' time series cumulative returns of P1 and P10 decile. Results in Figure 3 indicate that over-priced stocks exhibit favorable track record of past returns. Over-priced stocks are past 5 years and past 3 years winners. Thus, career concerned managers have motivation to choose over-priced stocks.

Finally, the limits-to-arbitrage literature provides one alternative explanation. Benchmarking is one limits-to-arbitrage for mutual funds. Baker, Bradley and Wurgler (2011) argue that the fact that typical mutual fund's mandate to beat a fixed benchmark discourages arbitrage activity, thus mutual funds do not exploit the low-volatility anomaly. Since A-score of stock is negatively related to the volatility as shown in Table 2, it is possible that we could apply their argument to explain why mutual funds do not exploit mispricing. Therefore, benchmarking as the limits-to-arbitrage also may play a role in explaining why mutual funds do not exploit stock market mispricing.

8. Conclusion

We study whether actively managed equity mutual funds exploit the stock market mispricing implied by fifteen well-known pricing anomalies. Although the existence of cross-sectional anomalies in the expected equity returns has been extensively documented in the literature, the literature does not explicitly examine mutual funds from this perspective. We define mispricing of stock using A-score which is the composite of fifteen pricing anomalies. Furthermore, to quantify how actively a fund follows the anomalies' implied mispricing strategy, we create the fund investing measure.

Our empirical evidence show that mutual funds on average do not follow the anomalies' implied mispricing. There is a tendency that majority of mutual funds over-weight for over-valued stocks. This adverse allocation to anomalies' implied mispricing may be one reason why on average mutual fund cannot beat the market given the anomalies' implied strategy generates superior risk-adjusted performance. We also show that the fund investing measure has some cross-sectional predictive power for future fund performance. For instance, the difference between the highest and lowest investing measure fund deciles is 2.39% per year in the three-factor risk adjusted performance. This finding implies that our investing measure is an alternative predictor for future fund returns. We further propose some rationales for why mutual funds do not exploit the stock market mispricing. We find that investment constraints of mutual funds and agency problem of managers are related with the behavior of fund managers.

Our results have implications for the growing debate on the portfolio delegation. In general, fund investors delegate their investments to fund managers, in the hope that it will benefit from managers' skills. However, our results raise the possibility that most mutual fund managers cannot beat the market due to investment constraints and agency problem of fund managers. Therefore, our findings cast some doubt on the existence of a large mutual fund industry.

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Appendix: Individual Anomalies

A.1. Anomaly Variable Definitions

A.1.1. Classical Group

Size (S)

Banz (1981) and Fama and French (1992) show that a firm's market cap is negatively related to its subsequent returns. Following Fama and French (2008), size is equal to the market value of equity *ME* = *PRC* * *SHROUT*, where *PRC* is the stock price, and *SHROUT* is the number of shares outstanding.

Book-to-Market (B/M)

Stattman (1980), Rosenberg, Reid and Lanstein (1985), and Fama and French (1992) show that book-to-market ratio is positively related to expected returns. Following Fama and French (2008), at the end of June of each year t, we calculate B/M as:

$$B/M = \frac{BE_{t-1}}{ME_{t-1}} = \frac{AT_{t-1} - LT_{t-1} + TXDITC_{t-1} - PS_{t-1}}{PRC * SHROUT}, \tag{A1}$$

where *BE* is the book value of equity at the fiscal year end in t-1, and *ME* is the market value of equity. Compustat *AT* is the total assets, Compustat *LT* is the total liabilities, Compustat *TXDITC* is deferred taxes and investment tax credit, and *PS* is the preferred stock value. Depending on the availability, *PS* is approximated by the liquidating value Compustat *PSTKL*, redemption value Compustat *PSTKRV*, or carrying value Compustat *PSTK* in this order of priority. *ME* is computed at the end of December of calendar year t-1.

Momentum (MOM)

The momentum effect is one of the most robust anomalies in asset pricing. It refers to the phenomenon that high past recent returns forecast high future returns. Jegadeesh and Titman (1993) show that past 3- to 12-months returns are positively related to subsequent 3- to 12-month returns. We use traditional 12-month momentum, defined as the cumulated continuously compounded stock return from month *t*-13 to month *t*-2, where *t* is the month of the forecasted return.

$$MOM_t = \prod_{s=t-13}^{t-2} (1 + RET_s) \tag{A2}$$

Month *t*-1 is skipped to control for the Jegadeesh (1990) and Lehmann (1990) short-term reversal. We measure the momentum variable monthly. To reduce the effect of bid-ask bounce on momentum, stocks with prices below or equal to $5 at the end of the previous month are excluded for the samples.

A.1.2. Investment

Asset growth (AG)

A variety of variables that measure firm growth or capital investment seem to be negatively related to future stock returns. Cooper, Gulen and Schill (2008) show that the growth in total assets has strong predictive power for future returns. They suggest that this phenomenon is due to investors' initial overreaction to changes in future business prospects implied by asset expansions. Following Cooper, Gulen and Schill (2008), at the end of June of each year t, asset growth is defined as the growth rate of firm's total assets in the previous fiscal year.

$$AG = \frac{AT_{t-1} - AT_{t-2}}{AT_{t-2}}, \tag{A3}$$

where Compustat *AT* is the total assets. To reduce the dataset errors, the sample of the *AG* is truncated each date by discarding the one percent of observations with the lowest and the one percent with the highest values of these variables.

Abnormal capital investment (CI)

Titman, Wei and Xie (2004) show that firms which increase capital investments earn negative subsequent returns. They attribute this anomaly to investors' initial under-reactions to the overinvestment caused by managers' empire building behavior. Following Titman, Wei and Xie (2004), we measure abnormal capital investment, at the end of June of each year t, as:

$$CI = \frac{CE_{t-1}}{(CE_{t-2} + CE_{t-3} + CE_{t-4})/3} - 1, \tag{A4}$$

where $CE = \frac{CAPX}{SALE}$ is capital expenditure (Compustat *CAPX*) scaled by its sales (Compustat *SALE*). The last three year average capital expenditure is used for the benchmark investment. To reduce the dataset errors, the sample of the *CI* is truncated each date by discarding the one percent of observations with the lowest and the one percent with the highest values of these variables.

Investment to assets ratio (I/A)

Lyandres, Sun and Zhang (2008) also show that higher past investment predicts abnormally lower future returns. Following Lyandres, Sun and Zhang (2008), at the end of June of each year t, we measure investment-to-assets ratio as changes in gross property, plant, and equipment (Compustat *PPEGT*) plus changes in inventory (Compustat *INVT*) scaled by lagged total assets (Compustat *AT*).

$$\mathrm{I/A} = \frac{PPEGT_{t-1} - PPEGT_{t-2} + INVN_{t-1} - INVT_{t-2}}{AT_{t-2}} \tag{A5}$$

A.1.3. Financing

Net stock issuance (NSI)

The stock issuing market has been long viewed as producing an anomaly arising from sentiment-driven mispricing. Pontiff and Woodgate (2008) and Fama and French (2008) show that there is a negative relation between net stock issues and average returns. Following Fama and French (2008), at the end of June of each year t, net stock issues is defined as the natural log of the ratio of the split-adjusted shares outstanding at the fiscal year end in t-1 divided by the split adjusted shares outstanding at the fiscal year end in t-2.

$$NS = lo\,g\left(\frac{SASO_{t-1}}{SASO_{t-2}}\right), \tag{A6}$$

where the split-adjusted shares outstanding is $SASO = CSHO * AJEX$, Compustat CSHO is the common shares outstanding, and Compustat $AJEX$ is the cumulative factor to adjust shares.

Composite stock issuance (CSI)

Many studies find that equity sales and repurchases have predictive power for future returns over both the short and long run. A common behavioral interpretation of such anomalies is that managers time equity markets by taking advantage of investor sentiment in their corporate finance decisions. Daniel and Titman (2006) study the composite equity issuance measure, defined as the amount of equity a firm issues (or retires) in exchange for cash or services. Under this measure, seasoned issues and share-based acquisitions increase the issuance measure, while repurchases, dividends, and other actions that take cash out of the firm reduce this issuance measure. They also find that issuers under-perform non-issuers. Following Daniel and Titman (2006), at the end of June of each year t, composite stock issuance is calculated as:

$$CSI = log\left(\frac{ME_{t-1}}{ME_{t-6}}\right) - r(t-6, t-1), \tag{A7}$$

where the market equity $ME_{t-1} = PRC * SHROUT$ at the end of December of fiscal year t-1, and $r(t-6, t-1)$ is the cumulative log return over the previous five years.

A.1.4. Accounting and Operating

Total accruals (ACC)

Sloan (1996) shows that accruals is strongly negatively related to subsequent returns, and suggests that investors overestimate the persistence of the accrual component of earnings when forming earnings expectations. Following Sloan (1996), at the end of June of each year t, accruals is defined as the change in net working capital minus depreciation scaled by average total assets for the previous two fiscal years:

$$ACC = \frac{(\Delta ACT_{t-1} - \Delta CHE_{t-1}) - (\Delta LCT_{t-1} - \Delta DLC_{t-1} - \Delta TXP_{t-1}) - DP_{t-1}}{ATA_{t-1}}, \quad \text{(A8)}$$

where Compustat *ACT* is the total current assets, Compustat *CHE* is cash and short-term investments, Compustat *LCT* is the total current liabilities, Compustat *DLC* is debt in current liabilities, Compustat *TXP* income taxes payable, Compustat *DP* is depreciation and amortization, Compustat *AT* is the total assets, and $ATA_{t-1} = \frac{AT_{t-1}+AT_{t-2}}{2}$ is average total assets for the previous two fiscal years. Here, $\Delta X_t = X_t - X_{t-1}$.

Net operating assets (NOA)

Hirshleifer, Hou, Teoh and Zhang (2004) find that the level of normalized net operating assets negatively predicts returns. They suggest that investors with limited attention tend to focus on accounting profitability, neglecting information about cash profitability, in which case net operating assets, equivalently measured as the cumulative difference between operating income and free cash flow, captures such a bias. Following Hirshleifer, Hou, Teoh and Zhang (2004), at the end of June of each year t, net operating assets is defined as:

$$NOA = \frac{Operating\ assets_{t-1} - Operating\ liabilities_{t-1}}{AT_{t-2}}, \quad \text{(A9)}$$

where

$$Operating\ assets_{t-1} = AT_{t-1} - CHE_{t-1}, \quad \text{(A10)}$$

$$Operating\ liabilities_{t-1} = AT_{t-1} - DLC_{t-1} - DLTT_{t-1} - MIB_{t-1} - PSTK_{t-1} - CEQ_{t-1} \quad \text{(A11)}$$

Compustat *AT* is the total assets, Compustat *CHE* is cash and short-term investments, Compustat *DLC* is debt in current liabilities, Compustat *DLTT* is the total long term debt, *MIB* is the minority interest, *PSTK* is the total preferred stock, and *CEQ* is the total common equity.

A.1.5. Profitability

Standardized unexpected earnings (SUE)

Post-Earnings Announcement Drift (PEAD) is the tendency for a stock's cumulative abnormal returns to drift in the direction of an earnings surprise for several weeks following an earnings announcement [e.g., Bernard and Thomas (1989)]. The resulting measure of unexpected earnings is often scaled by its historical standard deviation such as in Chan, Jegadeesh and Lakonishok (1996) and Chordia and Shivakumar (2006). Following the existing literature, we measure earnings surprise as Standardized Unexpected Earnings (*SUE*). We calculate *SUE* as the change in the most recently announced quarterly earnings per share from its value announced four quarters ago divided by the standard deviation of this change in quarterly earnings over the prior eight quarters. (We require a minimum of six quarters in calculating SUE.)

$$SUE_t = \frac{E_t - E_{t-4}}{\sigma_t}, \tag{A12}$$

where E_t is the most recently announced earnings, E_{t-4} is earnings in the same quarter of the previous year, and σ_t is the standard deviation of the difference $(E_t - E_{t-4})$ over the prior eight quarters.

Return on assets (ROA)

Many studies find that find that more profitable firms have higher expected returns than less profitable firms [e.g., Fama and French (2006); Novy-Marx (2013)]. Wang and Yu (2013) find that the anomaly exists primarily among firms with high arbitrage costs and high information uncertainty. We measure profitability as return on asset (*ROA*) following Wang and Yu (2013).

$$ROA = \frac{IBQ_t}{ATQ_{t-1}} \tag{A13}$$

ROA is calculated as income before extraordinary (Compustat IBQ) divided by one-quarter-lagged total assets (Compustat ATQ).

A.1.6. Uncertainty about firm

Idiosyncratic volatility (IVOL)

If investors demand compensation for not being able to diversify risk, then agents will demand a premium for holding stocks with high idiosyncratic volatility. However, Ang, Hodrick, Xing and Zhang (2006) find that past idiosyncratic volatility is a strong negative predictor of subsequent returns. Their results on idiosyncratic volatility represent a substantive puzzle. Following Ang, Hodrick, Xing and Zhang (2006), we measure a stock's idiosyncratic volatility (IVOL) as the standard deviation of the residuals from regressing the stock's returns in excess of the one-month Treasury bill rate on the four factors in month t. (We require a minimum of 15 daily stock returns.)

$$RET_t^d - RF_t^d = \alpha + \beta_t^{MKTRF} MKTRF_t^d + \beta_t^{SMB} SMB_t^d + \beta_t^{HML} HML_t^d + \beta_t^{UMD} UMD_t^d + \epsilon_t^d \tag{A14}$$

where RET_t^d and RF_t^d are the daily stock return and one-month Treasury bill rate, respectively. $MKTRF_t^d$, SMB_t^d, and HML_t^d are daily Fama and French (1993), and UMD_t^d is the daily Carhart (1997) momentum factor. To reduce the effect of bid-ask bounce, stocks with prices below or equal to $5 at the end of the previous month are excluded for the samples.

Ohlson's O-score (OSC)

Financial distress is often invoked to explain otherwise anomalous patterns in the cross section of stock returns. However, Ohlson (1980) find that firms with high probability of bankruptcy have lower, not higher, subsequent returns. The Ohlson O-score is calculated as the probability of bankruptcy in a static model using accounting variables, such as net income divided by assets, working capital divided by market assets, current liability divided by current assets, etc. Following Ohlson (1980), in each end of the quarter t, the O-score is calculated as:

$$O-Score_t = -1.32 - 0.407\,log(Size_t) + 6.03TLTA_t - 1.43WCTA_t + 0.076CLCA_t - 1.72OENEG_t - 2.37NITA_t - 1.83FUTL_t + 0.285INTWO_t - 0.521CHIN_t\,, \tag{A15}$$

where $Size_t = \frac{ATQ_t}{CPI_t}$ is total assets adjusted for inflation, where ATQ_t is the total assets from Compustat, and CPI_t is the consumer price index form the U.S. Bureau of Labor Statistics. $TLTA_t = \frac{DLCQ_t + DLTTQ_t}{ATQ_{t-1}}$ is the total liabilities divided by lagged total assets, where Compustat $DLCQ_t$ is debt in current liabilities, Compustat $DLTTQ_t$ is total long term debt. $WCTA_t = \frac{ACTQ_t - LCTQ_t}{ATQ_{t-1}}$ is working capital divided by lagged total assets, where Compustat $ACTQ_t$ is current assets, Compustat $LCTQ_t$ is current liabilities. $CLCA_t = \frac{LCTQ_t}{ACTQ_t}$ is current liabilities divided by current assets. $OENEG_t$ is one if total liabilities exceeds total assets and zero otherwise. $NITA_t = \frac{NIQ_t}{ATQ_{t-1}}$ is net income divided by lagged total assets, where Compustat NIQ_t is net income. $FUTL_t = \frac{PIQ_t}{LTQ_{t-1}}$ is funds provided by operations divided by lagged total liabilities, where Compustat PIQ_t is pretax income. $INTWO_t$ is one if net income was negative for the last who years and zero otherwise. $CHIN_t = \frac{NIQ_t - NIT_{t-1}}{|NIQ_t| + |NIQ_{t-1}|}$ is level adjusted change in net income.

Dispersion in analysts' earnings forecasts (DISP)

Several approaches arrive at the conclusion that stocks with high differences of opinion tend to underperform. Diether, Malloy and Scherbina (2002) uncover that dispersion in analysts' earnings forecasts negatively predicts returns. This is inconsistent with an interpretation of dispersion in analysts' forecasts as a proxy for risk. Following Diether, Malloy and Scherbina (2002), we measure analyst earnings forecasts dispersion (*DISP*) as the ratio of the standard deviation of earnings forecast (I/B/E/S unadjusted file, item STDEV) to the absolute value of the consensus mean forecast (I/B/E/S unadjusted file, item MEANEST).

$$DISP = \frac{\sigma(e_t)}{|\bar{e_t}|}\,, \tag{A16}$$

where $\bar{e_t}$ and $\sigma(e_t)$ are the average and standard deviation of I/B/E/S next quarter analysts' earnings forecast, respectively.

A.2. Average Returns of Anomaly-based Portfolios

In this subsection, we provide some descriptive evidence on the performance of the anomaly strategies. Table A.1 presents the list of the fifteen stock return anomalies we examine.

< Insert Table A.1 >

Our construction of the anomaly portfolios starts in June of 1982 since our mutual fund sample begins in 1982. As a result, the sample period for anomaly portfolio returns extends from July 1982 through June 2012. We follow standard conventions in the literature for constructing anomaly portfolios. For each anomaly, we compute the traditional long-short zero-cost portfolio approach based on some form of percentile placement. We construct a long portfolio with the seemingly most undervalued securities (highest-performing 30% for the ranking variable as of formation date) and a corresponding short portfolio with the most overvalued stocks (lowest-performing 30% for the ranking variable as of formation date). Following prior studies, frequencies of rebalancing are different across anomalies. Specifically, size, book-to-market, total asset growth, abnormal capital investments, investments-to-assets ratio, net stock issues, composite stock issuance, accruals, and net operating assets are updated annually at the end of June. Standardized unexpected earnings, return on assets, and O-score are updated quarterly, and momentum, idiosyncratic volatility, and dispersion in analysts' forecasts are updated monthly.

For annually rebalanced anomalies, we form portfolios at the end of each June in year t using data observed from the fiscal year ending in calendar year t-1, and hold the stocks for twelve months from July t through June t+1. In the case of quarterly rebalanced anomalies, we rank stocks at the end of each calendar quarter t using accounting data from the fiscal quarter ending in calendar quarter t-1 and hold them for three months. For the momentum, at the beginning of each month t, we use the NYSE breakpoints to split all NYSE, Amex, and NASDAQ stocks into deciles based on their prior twelve-month returns from month $t-13$ to $t-2$. Skipping month $t-1$, we calculate monthly portfolio returns from month t to t+11. For the idiosyncratic volatility and dispersion in analysts' forecasts, we form portfolios every month and hold the portfolio during one month.

Table A.2 provides equally-weighted average returns of the long-short portfolios along with the t-statistics for the null hypothesis that the average returns equal zero. We report raw returns, as well as abnormal returns relative to the Fama and French (1993) three-factor model.

< Insert Table A.2 >

Panel A of Table A.2 presents average raw annual returns for each anomaly. Panel A shows that most of the 15 strategies, each purchasing stocks in the long leg and shorting stocks in the short leg, are highly significant both statistically and economically, confirming the presence of anomalies during our sample period. Among statistically significant anomalies, the annual raw returns are in the range from 2.52 percent per year (t-stat=2.41) for the abnormal capital investment anomaly to 10.41 percent (t-stat=4.83) for the book-to-market anomaly. For the size and O-score based anomalies, the long leg does not reliably outperform the short leg in our sample.

Turning to abnormal return, in Panel B, we find strong positive alphas relative to the Fama and French (1993) three-factor model in most cases. We find that accruals and O-score are not significant at the 10% level, whereas all other anomalies are significant at the 1% level. The reason is that the characteristic-return relation tends to be nonlinear with the most variation coming from extreme 10% performing portfolio. When repeating our analysis by changing the definition of long/short leg, long portfolio with highest-performing 10% and short portfolio with lowest-performing 10%, the long leg significantly outperforms the short leg for all fifteen anomalies.[8]

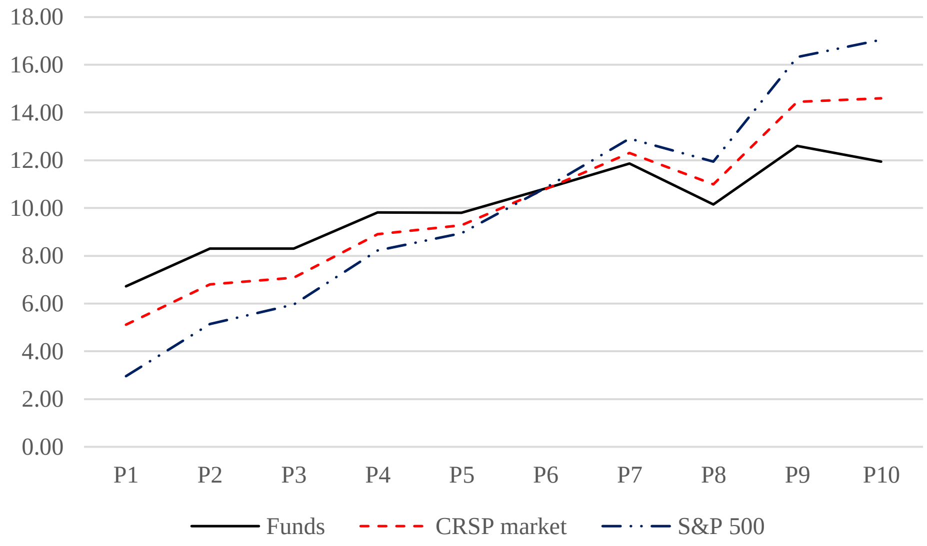
Overall, the results suggest that all examined characteristics are different from the two prominent anomalies forming the basis for the most popular factor model of Fama and French (1993). The abnormal return may reflect either mispricing or benchmark errors. There is also a well-known debate over whether particular anomalies are due to risk or mispricing [e.g., Fama and French (1993); Daniel and Titman (1997); Daniel, Hirshleifer and Subrahmanyam (1998)]. However, such a distinction is not likely relevant to mutual fund managers who are almost uniformly evaluated against these benchmarks. Hence, we take the position that cross-sectional predictability based on anomalies is at least in part due to cross-sectional mispricing in equity markets.

8 The results of this analysis are not presented here for brevity.

Figure 1. Portfolio Weights of Average Mutual Fund across A-score Sorted Stock Deciles.

This figure shows portfolio weights in each A-score sorted stock deciles for Fund, CRSP market portfolio, and S&P500 portfolio over June 1982 to June 2011. In Panel A, the portfolio weights in each stock A-score decile for each portfolio are reported. The portfolio weight of a stock A-score decile is the total value of the stocks in the A-score decile held by each portfolios divided by the total value of the portfolio. In Panel B, we report the difference of portfolio weights between fund portfolio and stock portfolio.

Panel A: Average Portfolio Weights



Panel B: Difference of Portfolio Weights

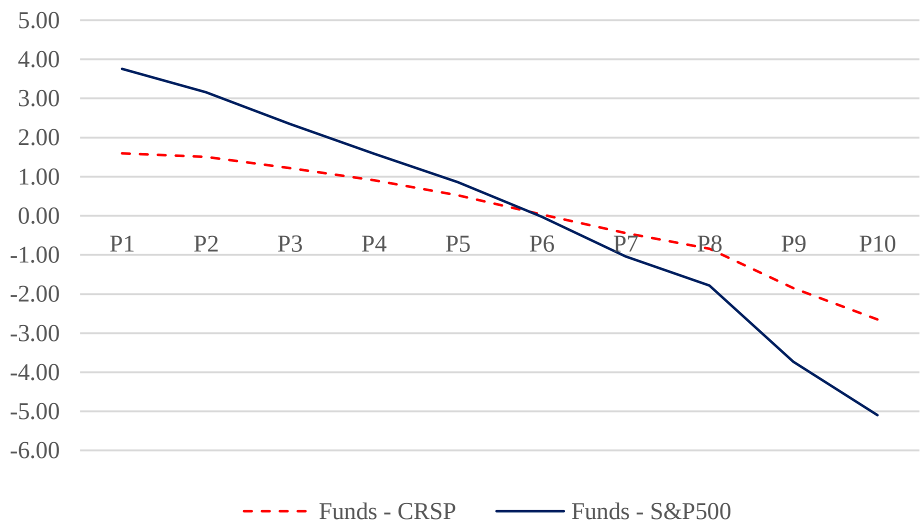
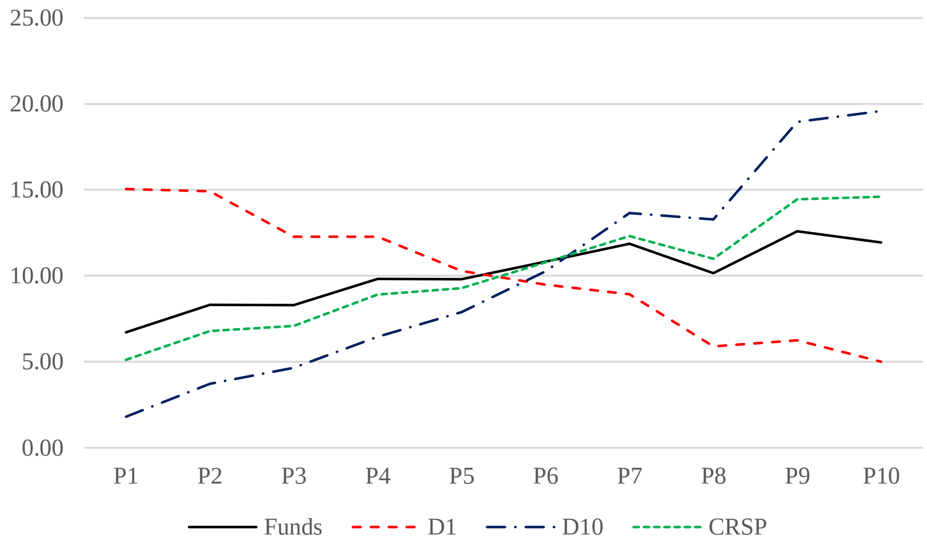


Figure 2. Portfolio Weights of D1 and D10 Funds across A-score Sorted Stock Deciles

This figure shows portfolio weights in each A-score sorted stock deciles for D1 funds and D10 funds over June 1982 to June 2011. In Panel A, the portfolio weights in each stock A-score decile for each portfolio are reported. The portfolio weight of a stock A-score decile is the total value of the stocks in the A-score decile held by each portfolios divided by the total value of the portfolio. In Panel B, we report the difference of portfolio weights between fund portfolio and stock portfolio.

Panel A: Average Portfolio Weights



Panel B: Difference of Portfolio Weights

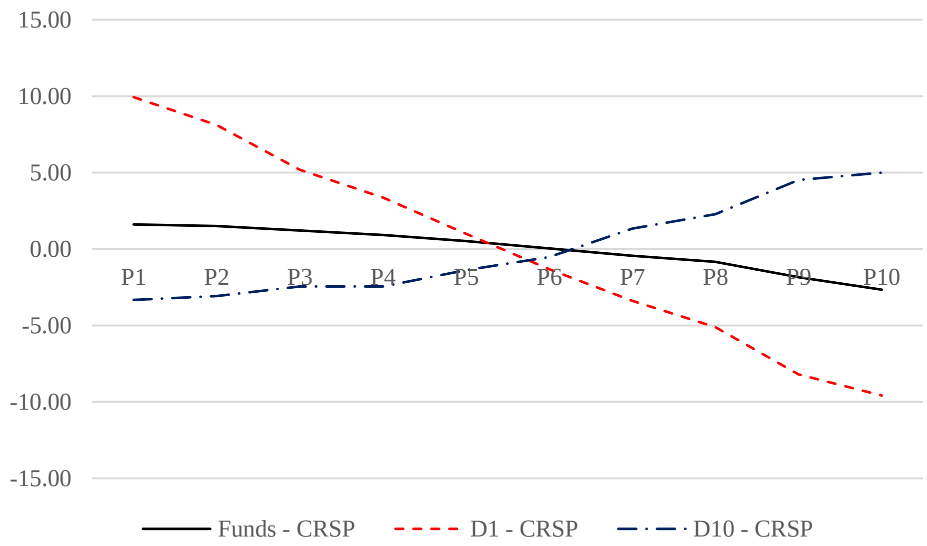
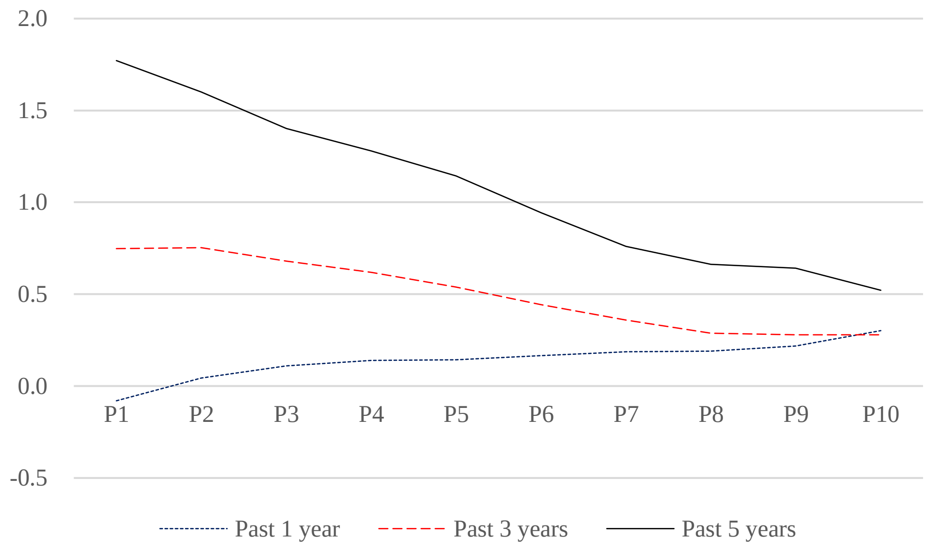


Figure 3. Long-term past cumulative returns of over-priced stocks.

This figure shows average lone-term past cumulative returns of each A-score sorted stock deciles over June 1982 to June 2011. Panel A display that the average 1-year, 3-years, and 5 years past cumulative returns of each A-score stock decile. Panel B shows that past 60-months' time series cumulative returns of P1 and P10 decile. Time 0 refers the formation date of A-score sorted stock deciles.

Panel A: Average past cumulative returns across A-score stock deciles.



Panel B: Time series of cumulative return for P1 and P10.

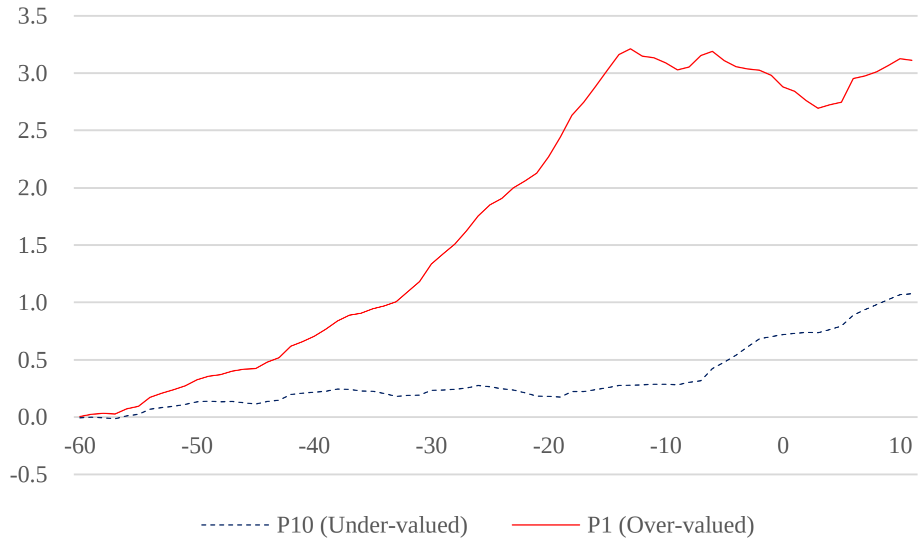


Table 1. Summary Statistics for Sample Mutual Funds

This table provides summary statistics for the sample of actively managed U.S. equity mutual funds in the Thomson Financial/CDA holdings data and CRSP fund returns data. The sample period is from 1982 to 2011. Fund total net assets, annual returns, turnover, expense ratio, and fund age are obtained from CRSP. Fund age is number of years since fund organization. Data on numbers of stocks held by funds are from Thomson Financial/CDA. 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

	1982~2011	1982	1985	1990	1995	2000	2005	2011
Number of Funds	3,268	196	276	444	1,022	1,808	1,950	1,594
Total Net Assets ($ Millions)	926.60	202.90	307.96	420.38	761.43	1495.17	1360.22	1428.95
Net Return (%/year)	11.95	46.92	26.85	-3.01	28.13	0.26	7.27	-58.18
Annual Turnover (%)	86.21	71.43	75.86	77.14	79.82	105.30	85.58	74.92
Annual Expense Ratio (%)	1.17	0.87	0.95	1.16	1.21	1.28	1.30	1.15
Fund Age (year)	15.99	22.99	22.35	19.07	12.91	11.32	13.29	17.20
Number of stocks held - mean	106	60	74	86	112	114	125	141
Number of stocks held - median	68	50	58	56	70	72	77	75

Table 2. Returns and Characteristics across A-Score Sorted Stock Deciles

This table reports the average returns and characteristics in A-score sorted decile portfolio for stocks in stock universe and for stocks held by our sample of mutual funds. The sample period is 1982-2012. A-score decile portfolio formed in each June of year t based on their A-score. P1 (P10) contains stocks with the lowest (highest) values of A-score. Return is mean raw returns of equal-weighted portfolio. Alpha is Fama-French (1993) three-factor annualized alpha. Size is the market capitalization. Market beta is obtained from the Fama-French (1993) three-factor model. Return volatility is the annualized standard deviation of monthly portfolio returns. Idiosyncratic volatility is the annualized standard deviation of estimated monthly portfolio return residuals from the Fama-French three-factor model. Heteroscedasticity-adjusted t-statistics are in parentheses.

	Stock Universe							Stocks Held by Mutual Funds						
Decile Portfolio	A-Score	Return (%)	Alpha (%)	Size ($ million)	Market Beta	Volatility (%)	Ivol (%)	A-Score	Return (%)	Alpha (%)	Size ($ million)	Market Beta	Volatility (%)	Ivol (%)
P1	-6.84	3.48	-11.40	829	1.24	28.05	43.53	-6.79	6.76	-9.42	958	1.23	27.03	39.94
		(0.74)	(-6.33)						(1.34)	(-5.55)				
P2	-4.14	8.03	-6.84	999	1.13	24.38	31.43	-4.08	11.48	-4.61	1193	1.15	23.55	27.58
		(1.83)	(-4.49)						(2.46)	(-2.90)				
P3	-2.64	11.83	-3.05	1192	1.10	23.06	28.42	-2.61	15.93	-0.35	1513	1.13	22.90	26.22
		(2.73)	(-1.94)						(3.44)	(-0.23)				
P4	-1.46	12.71	-1.63	1337	1.07	22.92	30.22	-1.45	16.50	0.82	1614	1.10	22.51	27.50
		(2.93)	(-1.20)						(3.69)	(0.62)				
P5	-0.41	14.13	-0.09	1427	1.00	21.68	29.12	-0.43	16.39	0.44	1673	1.06	21.26	24.36
		(3.31)	(-0.06)						(3.63)	(0.34)				
P6	0.60	16.07	1.97	1633	1.02	21.86	29.74	0.59	18.60	3.26	2035	1.05	21.52	27.76
		(3.80)	(1.20)						(4.27)	(1.88)				
P7	1.68	18.70	4.54	1949	0.99	20.92	27.81	1.70	20.07	4.47	2578	1.05	20.32	22.95
		(4.43)	(2.83)						(4.67)	(3.00)				
P8	2.77	18.81	4.71	1846	0.96	20.91	28.89	2.79	20.51	5.12	2482	1.01	20.55	24.84
		(4.47)	(2.85)						(4.76)	(3.05)				
P9	4.02	18.78	5.00	2309	0.92	20.00	29.81	4.01	19.59	4.77	3065	0.96	19.13	22.83
		(4.43)	(3.28)						(4.63)	(3.65)				
P10	6.17	20.01	6.91	2812	0.84	17.47	24.68	6.18	19.94	5.65	3466	0.91	17.36	22.53
		(5.39)	(5.19)						(5.24)	(4.40)				
P10 - P1		16.53	18.31						13.19	15.07				
		(6.88)	(9.11)						(5.34)	(9.47)				

Table 3. Portfolio Characteristics of Average Mutual Fund

This table presents mean value of portfolio investing measure, portfolio characteristic scores of individual anomaly, and portfolio weights across A-score sorted stock deciles over June 1982 to June 2011. "Fund" indicates the fund portfolio in the aggregate, where we pool the equity holdings of all funds into a portfolio. For the fund portfolio, a stock's weight is the percent of the portfolio's value invested in the stock. "CRSP Stocks" refers to a portfolio of all common stocks in the CRSP database with non-missing A-score computed using CRSP, COMPUSTAT and I/B/E/S data. "S&P500" denote a portfolio of S&P500 stocks. For the stock portfolio, capitalization-weight is used as a stock's weight. In Panel A, the time-series average for portfolio characteristics of each portfolio are reported. In Panel B, the portfolio weights in each stock A-score decile for each portfolio are reported. Numbers in parentheses are t-statistics.

Panel A: Average Funds Portfolio Characteristics

	Funds	CRSP Stocks	S&P500	Funds - CRSP		Funds - S&P500	
Investing Measure	4.50	6.44	6.82	-1.93	(-14.57)	-2.32	(-15.44)
ME score	4.66	2.25	1.38	2.42	(31.86)	3.29	(49.70)
BM Score	2.83	3.84	3.74	-1.01	(-6.25)	-0.91	(-4.96)
MOM Score	4.58	5.76	5.82	-1.18	(-6.32)	-1.24	(-5.83)
AG Score	6.21	4.95	5.04	1.26	(12.54)	1.17	(10.31)
CI Score	7.01	5.65	5.48	1.36	(14.56)	1.53	(15.04)
IA Score	6.59	5.38	5.51	1.20	(12.83)	1.08	(9.90)
NS Score	6.91	6.09	6.40	0.82	(6.06)	0.51	(3.44)
CSI Score	7.22	6.40	6.30	0.82	(7.23)	0.92	(7.28)
ACC Score	7.22	6.19	6.33	1.03	(13.76)	0.89	(10.43)
NOA Score	7.97	7.20	7.52	0.76	(6.66)	0.45	(3.60)
SUE Score	4.48	5.81	6.05	-1.33	(-15.55)	-1.57	(-16.01)
ROA Score	4.90	6.48	6.79	-1.59	(-20.07)	-1.89	(-21.19)
IVOL Score	8.36	8.07	8.49	0.29	(2.72)	-0.14	(-1.24)
OSC Score	9.05	8.93	9.66	0.12	(2.45)	-0.61	(-12.17)
DISP Score	7.88	7.23	7.30	0.65	(9.59)	0.58	(7.32)

Panel B: Portfolio Weights

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
Funds	6.72	8.31	8.30	9.81	9.80	10.82	11.87	10.16	12.60	11.94
CRSP	5.12	6.80	7.08	8.90	9.28	10.79	12.31	11.00	14.44	14.59
S&P500	2.97	5.15	5.95	8.23	8.95	10.85	12.91	11.94	16.33	17.04
Funds - CRSP	1.60	1.51	1.22	0.91	0.52	0.03	-0.44	-0.84	-1.85	-2.65
	(2.65)	(1.80)	(1.34)	(1.02)	(0.89)	(0.04)	(-0.55)	(-0.94)	(-1.15)	(-1.56)
Funds – S&P500	3.76	3.16	2.35	1.59	0.86	-0.02	-1.04	-1.78	-3.73	-5.10
	(6.43)	(3.57)	(2.48)	(1.68)	(1.26)	(-0.02)	(-1.19)	(-1.76)	(-2.07)	(-2.53)

Table 4. Portfolio Weights of Investing Measure Sorted Fund Deciles across A-score Sorted Stock Deciles

This table shows portfolio weights in each A-score sorted stock deciles for investing measure sorted fund deciles over June 1982 to June 2011. D1 is the decile with the lowest investing measure funds and D10 is the decile with highest investing measure funds. The portfolio weights in each stock A-score decile for each portfolio are reported. The portfolio weight of a stock A-score decile is the total value of the stocks in the A-score decile held by each portfolios divided by the total value of the portfolio. We also report the difference of portfolio weights between D1 (D10) fund portfolio and CRSP market portfolio.

Fund Decile	Stock A-Score Decile									
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
D1	15.05	14.91	12.27	12.27	10.29	9.48	8.92	5.89	6.26	5.00
D2	12.33	13.05	11.62	11.64	10.65	10.19	9.49	7.08	8.36	5.96
D3	10.18	11.86	10.53	11.62	10.74	10.72	10.68	7.98	8.85	7.21
D4	8.47	10.30	9.38	11.22	10.87	10.79	11.45	9.30	9.94	8.65
D5	7.08	8.99	9.04	10.44	10.85	11.14	11.62	9.54	11.49	10.18
D6	5.67	7.67	8.28	9.95	10.08	11.13	12.39	10.57	12.55	12.05
D7	5.20	6.69	7.63	9.40	9.64	11.60	12.12	11.18	13.59	13.29
D8	4.23	5.84	6.56	8.76	8.98	10.94	13.22	11.60	14.94	15.22
D9	2.96	5.20	5.91	7.73	8.75	10.86	13.17	12.26	16.34	17.12
D10	1.80	3.73	4.64	6.46	7.89	10.27	13.65	13.28	18.95	19.59
All Funds	6.72	8.31	8.30	9.81	9.80	10.82	11.87	10.16	12.60	11.94
CRSP	5.12	6.80	7.08	8.90	9.28	10.79	12.31	11.00	14.44	14.59
Fund - CRSP	1.60	1.51	1.22	0.91	0.52	0.03	-0.44	-0.84	-1.85	-2.65
	(2.65)	(1.80)	(1.34)	(1.02)	(0.89)	(0.04)	(-0.55)	(-0.94)	(-1.15)	(-1.56)
D1 - CRSP	9.93	8.12	5.18	3.37	1.01	-1.31	-3.39	-5.11	-8.19	-9.59
	(8.00)	(7.59)	(4.47)	(3.17)	(1.75)	(-1.30)	(-4.10)	(-6.57)	(-5.82)	(-6.45)
D10 - CRSP	-3.32	-3.07	-2.44	-2.44	-1.39	-0.52	1.34	2.28	4.51	5.00
	(-7.61)	(-4.19)	(-3.07)	(-2.96)	(-1.98)	(-0.55)	(1.48)	(1.91)	(2.45)	(2.29)

Table 5. Fund Performance across Investing Measure Sorted Fund Deciles

This table presents the mean value of fund performance measure from 1982 to 2011. For each June of year t, we rank mutual funds into deciles base on their investing measure. D1 is the decile with the lowest investing measure funds and D10 is the decile with highest investing measure funds. Fund performance measures are raw return, Fama-French (1993) three factor alpha, Carhart (1997) four factor alpha, and Sharpe ratio, both before and after fund expenses. We also report the volatility for each fund deciles. Heteroscedasticity-adjusted t-statistics are in parentheses.

Fund Decile	Fund Performance Before Fees					Fund Performance After Fees				
	Raw Return	3-Factor Alpha	4-Factor Alpha	Sharpe Ratio	Volatility	Raw Return	3-Factor Alpha	4-Factor Alpha	Sharpe Ratio	Volatility
D1	12.17	-0.94	-0.68	0.42	18.38	10.89	-2.23	-1.77	0.36	18.38
	(3.62)	(-1.30)	(-0.97)	(2.32)		(3.24)	(-3.08)	(-2.44)	(1.94)	
D2	12.77	0.02	-0.11	0.45	18.72	11.53	-1.22	-1.35	0.38	18.72
	(3.73)	(0.04)	(-0.18)	(2.45)		(3.37)	(-1.96)	(-2.15)	(2.09)	
D3	12.88	0.05	-0.11	0.47	17.99	11.66	-1.17	-1.33	0.41	17.99
	(3.91)	(0.08)	(-0.19)	(2.58)		(3.54)	(-2.01)	(-2.25)	(2.21)	
D4	12.75	0.11	0.03	0.49	17.19	11.56	-1.08	-1.16	0.42	17.19
	(4.05)	(0.20)	(0.05)	(2.66)		(3.67)	(-2.00)	(-2.11)	(2.29)	
D5	12.68	-0.08	-0.07	0.50	16.58	11.53	-1.23	-1.23	0.43	16.59
	(4.18)	(-0.15)	(-0.14)	(2.73)		(3.80)	(-2.37)	(-2.32)	(2.36)	
D6	12.16	-0.33	-0.35	0.49	15.89	11.05	-1.45	-1.46	0.42	15.89
	(4.18)	(-0.72)	(-0.74)	(2.68)		(3.80)	(-3.18)	(-3.16)	(2.30)	
D7	12.45	0.24	0.30	0.53	15.27	11.38	-0.84	-0.78	0.46	15.27
	(4.46)	(0.57)	(0.71)	(2.89)		(4.07)	(-2.05)	(-1.87)	(2.51)	
D8	12.12	0.00	-0.05	0.51	15.13	11.04	-1.08	-1.13	0.44	15.14
	(4.37)	(0.01)	(-0.11)	(2.79)		(3.98)	(-2.62)	(-2.69)	(2.41)	
D9	12.65	0.67	0.51	0.55	14.94	11.57	-0.41	-0.57	0.48	14.94
	(4.62)	(1.61)	(1.21)	(3.02)		(4.23)	(-0.98)	(-1.36)	(2.63)	
D10	12.63	0.97	0.87	0.58	14.14	11.56	-0.10	-0.20	0.51	14.15
	(4.87)	(2.07)	(1.83)	(3.18)		(4.46)	(-0.22)	(-0.43)	(2.77)	
All	12.53	0.07	0.03	0.50	16.24	11.38	-1.08	-1.10	0.43	16.24
	(4.21)	(0.18)	(0.12)	(2.74)		(3.83)	(-2.76)	(-2.76)	(2.36)	
D10-D1	0.46	1.91	1.55			0.67	2.12	1.56		
	(0.34)	(2.14)	(1.81)			(0.49)	(2.38)	(1.75)		

Table 6. Regression Analysis of Fund Performance

This table presents regression evidence of the predictability of performance based on fund investing measure. For each June of year t, we calculate fund investing measure. Fund performance measures are Fama-French (1993) three factor alpha, and Carhart (1997) four factor alpha, both before and after fund expenses, measured from July of year t to June of year t+1. The results for the multivariate regressions including a number of fund characteristics control variables all as of June of year t. Log TNA is the natural log of TNA. Log age is the natural log of the number of years since the fund was first offered plus one. Expense ratio is the ratio of the total investment that shareholders pay for the fund's operating expenses. Turnover ratio is the minimum of aggregated sales or aggregated purchase of securities, divided by the 12-month total net assets of the fund. Past performance is fund performance measured from July of year t-1o June of year t. Flow is sum of previous four quarters flow, where quarterly flow is measure as the percentage growth of the fund's assets, after adjusting for the appreciation of the mutual fund's assets assuming that all cash flows are invested at the end of the quarter. Active share is computed as following Petajisto (2013). Tracking error is computed as the standard deviation of the difference between monthly fund returns and its benchmark index returns, measured from July of year t-1 to June of year t. R-square is obtained from Carhart four-factor model with twenty-four-month estimation period. All specifications include year dummies. Regressions are estimated using robust estimator of variance cluster at fund level. Numbers in parentheses are t-statistics.

	Fund Return Before Fees						Fund Return After Fees					
	3-Factor Alpha			4-Factor Alpha			3-Factor Alpha			4-Factor Alpha		
Investing Measure	0.171	0.175	0.373	0.288	0.270	0.535	0.233	0.182	0.379	0.345	0.276	0.540
	(2.64)	(2.72)	(3.47)	(4.39)	(4.04)	(5.23)	(3.58)	(2.81)	(3.50)	(5.20)	(4.10)	(5.27)
log(TNA)		-0.470	-0.754		-0.129	-0.448		-0.459	-0.753		-0.119	-0.446
		(-2.20)	(-2.84)		(-0.60)	(-1.77)		(-2.15)	(-2.83)		(-0.56)	(-1.76)
log(TNA)2		0.036	0.058		-0.001	0.032		0.036	0.058		-0.001	0.033
		(2.10)	(2.73)		(-0.08)	(1.57)		(2.09)	(2.76)		(-0.08)	(1.59)
log(Age+1)		-0.276	-0.281		-0.293	-0.441		-0.275	-0.277		-0.295	-0.437
		(-2.92)	(-2.27)		(-2.81)	(-3.62)		(-2.89)	(-2.23)		(-2.82)	(-3.58)
Expense Ratio		0.261	0.226		0.008	-0.224		-0.658	-0.628		-0.870	-1.011
		(1.32)	(0.86)		(0.04)	(-0.98)		(-3.15)	(-2.17)		(-4.28)	(-4.03)
Turnover Ratio		-0.006	-0.007		-0.004	-0.003		-0.006	-0.006		-0.004	-0.003
		(-5.39)	(-4.21)		(-4.18)	(-2.89)		(-5.02)	(-3.67)		(-3.78)	(-2.27)
Past Performance		-0.011	0.014		0.031	0.087		-0.011	0.015		0.031	0.088
		(-0.88)	(1.01)		(2.08)	(6.26)		(-0.83)	(1.08)		(2.12)	(6.32)
Flow		-0.012	-0.010		-0.009	-0.009		-0.012	-0.010		-0.009	-0.009
		(-5.43)	(-3.65)		(-4.07)	(-3.71)		(-5.35)	(-3.60)		(-4.00)	(-3.66)
Active Share			0.043			0.055			0.042			0.054
			(5.44)			(7.29)			(5.41)			(7.24)
Tracking Error			-0.200			-0.102			-0.204			-0.106
			(-3.92)			(-2.48)			(-3.98)			(-2.56)
R-Square			-0.028			0.023			-0.027			0.023
			(-1.66)			(1.32)			(-1.64)			(1.34)
Year Dummies	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Adj R^2	8.99	10.31	11.45	12.73	16.16	20.28	9.04	10.47	11.68	12.71	16.27	20.42

N	25,113	25,113	11,430	25,113	25,113	11,430	25,113	25,113	11,430	25,113	25,113	11,430

Table 7. Determinant of Fund Investing Measure

Panel A reports the mean value of fund characteristics and characteristics of stocks held by funds across investing measure sorted fund deciles. For each year t, we rank mutual funds into decile based on investing measure. Fund characteristics are measured at the end of June of each year t. Panel B presents regression evidence of the determinant of fund investing measure. The sample period is 1982-2011.

Panel A: Fund characteristics across investing measure sorted fund deciles

	Fund Investing Measure Decile									
	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
Investing Measure	2.47	3.45	3.79	4.08	4.36	4.63	4.90	5.18	5.53	6.20
TNA ($ Millions)	653	734	850	877	872	1052	1113	979	860	614
Expense Ratio (%)	1.29	1.26	1.23	1.20	1.17	1.13	1.09	1.09	1.10	1.08
Turnover Ratio (%)	89.39	91.65	94.18	95.95	88.53	88.77	82.04	75.10	76.14	74.99
Fund Age (year)	13.91	14.19	15.18	14.35	15.63	16.45	17.36	17.23	17.18	17.20
Flow (%/year)	6.19	8.36	6.97	6.53	6.70	5.67	3.95	4.00	4.34	3.44
Number of stocks held	68	93	114	120	114	117	119	115	110	81
Market Beta	1.12	1.14	1.12	1.08	1.03	0.98	0.96	0.94	0.92	0.87
Cash holdings (%)	6.65	6.92	6.45	5.77	6.14	5.94	5.87	5.76	5.29	5.63
Active Share (%)	91.80	89.10	86.70	83.80	82.10	79.80	77.40	75.50	72.10	73.70
Tracking Error (%/year)	9.16	7.92	7.67	7.03	6.75	6.48	6.15	5.96	5.82	6.35
R-square (%)	84.13	89.68	90.15	90.36	90.68	91.04	91.39	91.94	91.78	88.95

Panel B: Regression analysis of fund investing measure

Model	log(TNA)	log(TNA)2	log(Age+1)	Expense Ratio	Turnover Ratio	Flow	Performance	Return Volatility	AS	AS^2	TE	TE^2	RSQ	RSQ^2	Adj R^2
(1)	-0.207	0.012	0.037	-36.750	0.004	-0.097	-0.148	-0.926							20.04
	(-4.77)	(3.50)	(1.50)	(-9.69)	(0.20)	(-3.83)	(-3.45)	(-26.89)							
(2)	-0.162	0.006	0.054	-21.743	-0.033	-0.100	0.267	-0.675	2.308	-3.082	0.257	0.535	1.558	-1.130	36.90
	(-3.82)	(1.82)	(2.42)	(-5.15)	(-1.62)	(-3.74)	(5.09)	(-15.29)	(5.42)	(-9.79)	(0.38)	(0.22)	(0.86)	(-1.05)	

Table 8. Transition Matrix for D1 and D10 Funds

This table presents the percentage of D1 (D10) funds that continue to remain in the D1 (D10) decile in the subsequent five years and the percentage of D1 funds that move to other investing measure deciles. For each year t, we rank mutual funds into decile based on investing measure, where investing measure is the weighted average of A-score decile ranks of individual stocks held by the mutual fund. D1 is the decile with the lowest investing measure funds and D10 is the decile with highest investing measure funds. The sample period is 1982-2011.

	D1 funds									
	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
year t	100.0									
year t+1	54.48	21.18	10.67	5.09	3.13	2.54	1.50	0.71	0.42	0.29
year t+2	45.85	20.13	11.03	7.27	5.02	4.04	2.49	1.88	1.13	1.17
year t+3	40.48	19.00	11.59	8.57	6.40	5.40	3.28	2.49	1.69	1.11
year t+4	37.57	19.29	10.95	9.35	7.16	5.86	4.56	2.66	0.95	1.66
year t+5	36.33	17.13	10.81	9.94	8.33	6.18	4.70	3.29	2.15	1.14
	D10 funds									
	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
year t										100.00
year t+1	0.20	0.45	0.61	0.85	1.66	2.84	5.43	10.17	21.92	55.88
year t+2	0.68	1.13	1.35	1.89	2.66	4.38	6.86	11.68	21.20	48.17
year t+3	1.42	1.88	2.13	3.50	3.80	5.22	8.72	12.47	20.02	40.85
year t+4	1.61	2.24	2.58	3.21	5.28	6.54	7.91	13.13	19.21	38.30
year t+5	1.47	2.62	3.26	3.97	5.44	7.49	9.15	13.69	18.17	34.74

Table 9. Regression Analysis of Investment Constraints

This table presents the results for regression of investment constraints. We use two proxies for investment constraints: market beta and cash holdings. All specifications include year dummies. Regressions are estimated using robust estimator of variance cluster at fund level. Numbers in parentheses are t-statistics.

Dependent	Cash Holdings			Market Beta		
Investing Measure	-0.4872	-0.3591	-0.2587	-0.0063	-0.0160	-0.0221
	(-6.35)	(-2.85)	(-1.97)	(-1.73)	(-7.16)	(-9.52)
log(TNA)	0.0275	-0.0130	-0.1099	0.0093	0.0030	0.0029
	(0.11)	(-0.04)	(-0.35)	(1.96)	(0.52)	(0.48)
log(TNA)2	0.0040	0.0187	0.0188	-0.0002	-0.0002	-0.0002
	(0.20)	(0.70)	(0.73)	(-0.53)	(-0.46)	(-0.42)
log(Age+1)	0.1473	0.1069	0.2269	-0.0028	0.0047	0.0055
	(1.21)	(0.65)	(1.48)	(-1.04)	(2.00)	(2.41)
Expense Ratio	0.6919	-0.0936	-0.1040	-0.0030	0.0243	0.0238
	(3.52)	(-0.37)	(-0.42)	(-0.49)	(4.86)	(4.75)
Turnover Ratio	0.0024	0.0017	0.0010	0.0000	0.0000	0.0000
	(2.46)	(1.27)	(0.81)	(-0.03)	(1.39)	(0.97)
Flow	0.0187	0.0214	0.0201	0.0000	0.0001	0.0001
	(12.12)	(9.71)	(9.85)	(-0.36)	(1.18)	(1.40)
Performance	-0.0012	-0.0080	0.0003	-0.0002	0.0004	0.0003
	(-0.18)	(-0.62)	(0.03)	(-1.42)	(2.01)	(1.69)
Return Volatility	-0.0578	-0.1088	-0.0932	0.0145	0.0143	0.0142
	(-7.17)	(-11.13)	(-10.16)	(119.04)	(90.96)	(86.10)
Return Gap			-0.0014			0.0002
			(-0.17)			(1.20)
Active Share		0.0511	0.0482		-0.0006	-0.0007
		(6.10)	(5.75)		(-4.12)	(-4.37)
Tracking Error		0.1875	0.1251		-0.0001	-0.0001
		(3.37)	(2.22)		(-0.17)	(-0.12)
RSQ		-0.0888	-0.0911		0.0067	0.0064
		(-3.94)	(-3.61)		(20.47)	(18.86)
Adj R^2	14.62	23.11	21.38	75.36	80.61	80.86
N	18,732	8,906	8,259	25,084	12,354	11,528

Table 10. Regression Analysis of Agency Costs

This table presents the results for regression of agency costs. We use three proxies for agency costs: expense ratio, return gap, and fund size. All specifications include year dummies. Regressions are estimated using robust estimator of variance cluster at fund level. Numbers in parentheses are t-statistics.

Dependent	Expense ratio			Return Gap			Fund Size		
Investing Measure	-0.0444	-0.0192	-0.0121	-0.8853	-0.8159	-0.5439	-0.1156	-0.2475	-0.2216
	(-7.44)	(-2.43)	(-1.67)	(-5.47)	(-3.38)	(-2.80)	(-5.75)	(-8.02)	(-6.70)
log(TNA)	-0.1007	-0.0863	-0.1033	-0.3716	-0.2519	-0.4995			
	(-4.67)	(-3.85)	(-4.60)	(-0.97)	(-0.45)	(-0.99)			
log(TNA)2	0.0019	0.0024	0.0033	0.0198	0.0152	0.0416			
	(1.16)	(1.29)	(1.83)	(0.63)	(0.34)	(1.01)			
log(Age+1)	-0.0234	-0.0482	-0.0358	-0.1122	-0.2935	0.0491	0.9119	0.8740	0.8434
	(-2.30)	(-4.30)	(-3.09)	(-0.62)	(-1.16)	(0.20)	(22.17)	(18.18)	(16.56)
Expense Ratio				-0.2613	-0.8371	-0.7603	-0.9441	-0.7513	-0.8494
				(-0.87)	(-1.39)	(-1.33)	(-14.37)	(-8.47)	(-8.09)
Turnover Ratio	0.0007	0.0009	0.0011	-0.0134	-0.0238	-0.0179	-0.0007	-0.0005	-0.0005
	(4.15)	(2.76)	(2.49)	(-5.02)	(-4.41)	(-3.91)	(-3.04)	(-1.26)	(-0.80)
Flow	0.0001	0.0002	0.0001	-0.0034	-0.0053	-0.0030	0.0071	0.0072	0.0062
	(0.84)	(1.59)	(0.45)	(-0.90)	(-0.98)	(-0.65)	(23.64)	(18.40)	(12.66)
Performance	0.0000	-0.0012	-0.0024	-0.0277	-0.0408	0.1479	0.0046	0.0066	0.0094
	(-0.14)	(-3.62)	(-3.89)	(-1.64)	(-1.66)	(5.09)	(7.57)	(7.21)	(4.91)
Return Volatility	0.0020	0.0009	-0.0012	-0.1237	-0.1679	0.0164	0.0013	0.0009	0.0007
	(6.04)	(1.85)	(-1.70)	(-8.87)	(-8.74)	(0.55)	(1.37)	(0.68)	(0.30)
Cash Holdings			-0.0003			-0.0071			0.0109
			(-0.35)			(-0.18)			(2.69)
Market Beta			0.1449			-2.7503			0.0548
			(3.96)			(-1.92)			(0.49)
Active Share		0.0049	0.0055		0.0929	0.0544		-0.0100	-0.0085
		(7.37)	(7.26)		(4.94)	(3.28)		(-4.63)	(-3.33)
Tracking Error		0.0080	0.0109		-0.1968	-0.2524		-0.0213	-0.0385
		(3.76)	(3.26)		(-1.74)	(-2.20)		(-3.04)	(-3.90)
RSQ		-0.0025	-0.0037		-0.0696	-0.0346		0.0145	0.0098
		(-2.47)	(-3.19)		(-2.10)	(-0.80)		(4.21)	(2.30)
Adj R^2	19.58	28.33	32.06	17.76	22.42	17.66	28.24	31.52	30.79
N	25,100	12,354	8,905	22,585	11,529	8,258	25,100	12,354	8,905

Table A.1. Anomalies Considered

This table reports a list of the fifteen stock return anomalies we examine, along with a primary literature reference. It also summarizes how each of the 15 characteristics is calculated and their relation to the future equity returns. (-) denotes that the characteristic is negatively related to future stock returns, and (+) means that the characteristic is positively related to future stock returns.

Anomaly	Citation	Ranking Variable	Future Returns
		Panel A. Classical Group	
Size (S)	Fama and French (2008)	$ME = PRC * SHROUT$	(-)
Book to market (B/M)	Fama and French (2008)	$B/M_t = \frac{AT_t - LT_t + TXDITC_t - PS_t}{ME_t}$	(+)
Momentum (MOM)	Jegadeesh and Titman (1993)	$MOM_t = \prod_{s=t-13}^{t-2} (1 + RET_s)$	(+)
		Panel B. Investment	
Asset growth (AG)	Cooper, Gulen, and Schill (2008)	$AG_t = \frac{AT_t - AT_{t-1}}{AT_{t-1}}$	(-)
Abnormal capital investment (CI)	Titman, Wei and Xie (2004)	$CI_t = \frac{CE_t}{(CE_{t-1} + CE_{t-2} + CE_{t-3})/3} - 1$	(-)
Investment to assets ratio (I/A)	Lyandres, Sun, and Zhang (2008)	$I/A_t = \frac{\Delta INVN_t + \Delta PPEGT_t}{AT_{t-1}}$	(-)
		Panel C. Financing	
Net stock issuance (NSI)	Pontiff and Woodgate (2008)	$NSI_t = log(\frac{SASO_t}{SASO_{t-1}})$	(-)
Composite stock issuance (CSI)	Daniel and Titman (2006)	$CSI_t = log\left(\frac{ME_t}{ME_{t-5}}\right) - r(t-5, t)$	(-)
		Panel D. Accounting and Operating	
Total accruals (ACC)	Sloan (1996)	$ACC_t = \frac{(\Delta ACT_t - \Delta CHE_t) - (\Delta LCT_t - \Delta DLC_t - \Delta TXP_t) - DP_t}{AT_t + AT_{t-1}/2}$	(-)
Net operating assets (NOA)	Hirshleifer, Hou, Teoh, and Zhang (2004)	$NOA_t = \frac{DLC_t + DLTT_t + MIB_t + PSTK_t + CEQ_t - CHE_t}{AT_{t-1}}$	(-)
		Panel E. Profitability	
Standardized unexpected earnings (SUE)	Bernard and Thomas (1989)	$SUE_t = \frac{E_t - E_{t-4}}{\sigma_t}$	(+)
Return on assets (ROA)	Wang and Yu (2013)	$ROA_t = \frac{IBQ_t}{ATQ_{t-1}}$	(+)
		Panel F. Uncertainty about firm	
Idiosyncratic volatility (IVOL)	Ang, Hodrick, Xing, and Zhang (2006)	Standard deviation of the residual from the daily four-factor time-series regression in month t.	(-)
Ohlson O-score (OSC)	Ohlson (1980)	Model 1 in Ohlson (1980)	(-)
Dispersion in analysts' earnings forecasts (DISP)	Diether, Malloy, and Scherbina (2002)	Standard deviation of next quarter analysts' earnings forecast, divided by average of next quarter analysts' earnings forecast	(-)

Table A.2. Anomaly Returns in Stock Market

This table presents annual returns in unit of percent between July 1982 and June 2012. Anomaly portfolios are held from July of year t through June of year t+1, consisting of a long position in Long leg stocks (highest-performing 30% for the ranking variable as of June year t) plus a short position in Short leg stocks (Lowest-performing 30%). The anomaly portfolio return is listed as Long – Short. Panel A reports mean raw returns of equal-weighted portfolio, Panel B presents three-factor alphas of equal-weighted portfolio. Three factor alphas refer to the intercept from a time-series regression of monthly excess returns (stock returns less the one month T-bill rate) on the MKT, SMB, HML factors (excluding S and B/M anomaly). Heteroscedasticity-adjusted t-statistics are in parentheses.

	S	B/M	MOM	AG	CI	I/A	NSI	CSI	ACC	NOA	SUE	ROA	IVOL	OSC	DISP
							Panel A: Raw returns								
Long Leg	15.12	19.70	17.19	18.91	16.60	17.27	16.71	16.49	15.95	17.58	19.20	17.82	14.44	14.27	14.76
	(3.28)	(4.57)	(4.33)	(3.90)	(3.82)	(3.70)	(4.76)	(5.48)	(3.51)	(3.59)	(5.13)	(5.26)	(5.54)	(3.13)	(4.98)
Short Leg	13.00	9.29	7.84	9.03	14.08	9.61	10.56	12.17	13.01	8.55	10.06	11.91	7.44	13.90	9.41
	(4.13)	(2.15)	(2.06)	(2.22)	(3.66)	(2.37)	(2.28)	(3.35)	(3.18)	(2.17)	(2.49)	(2.33)	(1.64)	(4.72)	(2.25)
Long-Short	2.12	10.41	9.36	9.88	2.52	7.65	6.15	4.31	2.93	9.03	9.14	5.91	7.00	0.37	5.34
	(0.72)	(4.83)	(3.27)	(5.38)	(2.41)	(5.10)	(2.95)	(2.45)	(2.66)	(3.80)	(6.06)	(2.08)	(2.21)	(0.13)	(2.22)
							Panel B: Three-factor alphas								
Long Leg			4.67	4.54	2.32	2.88	2.87	2.80	1.32	4.17	5.32	4.37	2.25	-0.14	2.35
			(3.80)	(2.00)	(1.50)	(1.58)	(2.28)	(2.56)	(0.75)	(1.94)	(4.82)	(3.85)	(2.10)	(-0.08)	(2.02)
Short Leg			-7.32	-4.94	-0.15	-4.86	-3.75	-2.40	-0.47	-5.90	-4.58	-3.03	-6.46	0.22	-5.61
			(-4.21)	(-3.92)	(-0.13)	(-3.61)	(-2.27)	(-1.97)	(-0.31)	(-4.00)	(-3.01)	(-1.43)	(-6.17)	(0.22)	(-4.55)
Long-Short			11.99	9.48	2.48	7.74	6.62	5.20	1.79	10.07	9.89	7.39	8.72	-0.36	7.96
			(4.53)	(4.65)	(2.60)	(4.81)	(4.26)	(4.33)	(1.42)	(4.30)	(8.04)	(3.37)	(5.21)	(-0.24)	(4.27)