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Do actively managed mutual funds exploit stock market mispricing?☆

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ABSTRACT

Constructing a proxy for mispricing with 15 well-known stock market anomalies, we examine whether actively managed mutual funds exploit mispricing. We find that, in the aggregate, mutual funds overweight overvalued stocks and underweight undervalued stocks relative to a passive benchmark, and this tendency is explained by the ill-motivated trades of agency-prone fund managers. In addition, we find that mutual funds with the highest weights in undervalued stocks outperform those with the highest weights in overvalued stocks by an annualized three-factor alpha of 2.12% (t = 2.38), implying that slanting portfolios based on our proxy helps mutual funds improve performance.

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 an important question: Why do actively managed funds underperform? The well-accepted answer 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 cross-sectional anomalies in expected equity returns.[2] Firm characteristics such as size, the book to market, past returns, investment, and profitability are well known to predict a

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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 initial publication. Green, Hand, and Frank Zhang (2013) identify more than 330 return-predictive signals and use 60 of them in their tests. Hou, Xue, and Zhang (2015) examine 80 anomalies. Jacobs (2015) explore 100 anomalies in the cross section of expected equity returns.

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firm's subsequent returns. Given the underperformance of mutual funds, our conjecture is that mutual funds, on average, hold overvalued stocks based on well-known anomalies. Using 15 well-known pricing anomalies, we study whether this is the case.

In our experiment, we make one important assumption. The existence of cross-sectional anomalies appears to violate the efficient market hypothesis, since seemingly less risky stocks generate higher future returns. These anomalies reflect either mispricing or model misspecifications. The assumption maintained in our paper is that cross-sectional anomalies are at least partly due to a mispricing effect in the equity market. Our assumption is supported by a recent paper by Stambaugh, Yu, and Yuan (Stambaugh et al., 2012) that documents a broad set of anomalies related to mispricing. From an efficient market point of view, if mutual fund managers are skilled, they construct trading strategies to exploit cross-sectional mispricing. Since mutual funds are typically constrained from engaging in short sales,[3] fund managers should invest in undervalued stocks and avoid overvalued stocks to exploit stock market mispricing.

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 in 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 each of the individual anomalies themselves could serve as a proxy for mispricing, we believe that they could be a noisy proxy for mispricing. To increase the precision of the proxy for mispricing, we attempt to diversify away some of the noise in each individual anomaly by aggregating the information embedded in each measure. To this end, for each stock, we combine the information associated with 15 well-known anomalies to construct their implied mispricing measure and define it as the stock's A-score. In addition, the A-score captures the fact that funds normally do not trade on single return predictability attributes. We find that our A-score captures cross-sectional mispricing well in the stock market; that is, stocks with a higher A-score are more likely to be undervalued and stocks with a low A-score are more likely to be overvalued.

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

Our empirical findings are summarized as follows. First, we find that, in the aggregate, mutual funds hold stocks with direction adverse to the anomalies' implied mispricing. The average mutual fund overweighs overvalued stocks and underweighs undervalued stocks relative to a passive benchmark. For instance, the portfolio weights of the funds in the most undervalued decile are 5.10% lower than those of the Standard & Poor's (S&P) 500 index (t = –2.53) and the portfolio weights of the funds in the most overvalued decile are 3.76% higher than those of the S&P 500 index (t = 6.43). In particular, funds with the lowest investing measure greatly overweight overvalued stocks relative to the benchmark. Our finding suggests that adverse allocation to anomalies' implied mispricing is one possible reason why, on average, mutual funds cannot beat the market, since the anomalies' implied mispricing strategy generates superior risk-adjusted performance in the stock market.

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

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

Our empirical findings raise a fundamental question. We find that funds that tilt their portfolios toward undervalued stocks earn higher risk-adjusted returns. However, we have shown that, in the aggregate, mutual funds hold stocks with a strongly persistent adverse direction of stock market mispricing. Why, then, do professional money managers tilt their portfolio toward overpriced stocks? One possible explanation is that overpriced stocks based on anomalies can be favorable for obtaining high fees. In fact, mutual funds that hold overvalued stocks require high expense ratios and take unobserved actions on funds compared to that have undervalued stocks. Furthermore, overvalued stocks have a high market beta which may be advantageous for management fees as suggested by Karceski (2002)'s agency model. We also observe that overvalued stocks typically have a favorable long-term history of past returns and, hence, could appear to be a safer choice as far as managers' personal career risks are concerned. Thus, funds' adverse allocation to mispricing could be caused by the ill-motivated trades of agency-prone fund managers.

Although the literature on stock market anomalies is vast, the literature does not explicitly examine mutual funds from this perspective. Only a few studies examine whether mutual fund managers trade on a specific market anomaly. Grinblatt et al. (1995) find evidence that mutual funds hold past winners and generate abnormal performance before expenses and transaction costs. Ali,

[3] Chen, Desai, and Krishnamurthy (2013) report that the proportion of mutual funds that actually use short sales in a given year was 2% in 1994, increasing to 7% in 2009.

Chen, Yao, and Yu (2008) examine the impact of the 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 a fundamental trading strategy, as suggested by Piotroski (2000). Ali, Chen, Yao, and Yu (2014) find evidence that mutual funds trade on a post-earnings announcement drift 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-attribute strategies, such as momentum or accruals, we combine the information associated with 15 pricing anomalies and investigate the more general question of whether mutual funds exploit stock market mispricing. Since funds normally do not trade on single return predictability attributes, our approach could be more appropriate for studying these issues. Second, unlike previous papers, we further investigate why professional money managers tilt their portfolio toward overpriced stocks.

Our paper is also related to works on the impact of institutional investors on market anomalies. Edelen, Ince, and Kadlec (2016), 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 alternative potential explanations of why mutual funds do not exploit mispricing and exacerbate mispricing in the stock market.

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. Section 5 investigates the relation between the anomalies' implied mispricing strategy and subsequent fund performance. Section 6 describes the characteristics of funds that trade aggressively on a strategy of the anomalies' implied mispricing and investigate the strategy's persistence. Section 7 suggests potential explanations for why mutual funds do not exploit stock market mispricing. Finally, Section 8 summarizes and concludes the paper.

2. Mutual fund and stock samples

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 Funds Holdings database maintained by Thomson Financial. Mutual fund returns and characteristics are obtained from the Center for Research in Security Prices (CRSP) Survivor-Bias-Free U.S. Mutual Fund Database. We combine the CRSP Survivor-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.

Thomson Financial compiled holdings are obtained from mandatory U.S. Securities and Exchange Commission (SEC) filings and from 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 a reported investment objective codes (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 Thomson 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 Thomson Financial data, since different share classes have the same holdings compositions. We aggregate all the observations pertaining to different share classes into one observation. We compute the sum of total net assets (TNA) in each share class to obtain the TNA in the fund. For the other fund quantitative attributes, such as the return, expense ratio, and turnover, we compute the value-weighted average across 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 the incubation bias of Evans (2010), we exclude observations whose observation year is prior to the reported fund-starting year and where the names of the funds are missing from the CRSP database. To reduce database errors, we exclude funds with TNA under $10 million, funds with fewer than 10 identified stock positions, and funds with a ratio of CRSP TNA to total market value of reported holdings below 50% or above 150%. We also require that the current date of fund holdings be no more than six months away from its previous fund holdings date.

The final matched database has 3966 distinct active U.S. 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 the representative years 1982, 1985, 1990, 1995, 2000, 2005, and 2011.

On average, the TNA of sample funds is $814.72 million, with an annual return of 12.19%, an annual turnover ratio of 86.79%, and an annual expense ratio of 1.20%. The average fund age is 14.85 years. The average number of stocks held in a fund is 113 and the median is 66. The number of funds increases from 196 in 1982 to 1687 in 2011.

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

Table 1
Summary statistics for sample mutual funds.

	1982–2011	1982	1985	1990	1995	2000	2005	2011
Number of Funds	3966	196	276	444	1022	1808	1950	1687
Total Net Assets ($ millions)	814.72	202.90	307.96	420.38	761.43	1495.17	1360.22	1297.62
Net Return (%/year)	12.19	46.92	26.85	−3.01	28.13	0.26	7.27	13.08
Annual Turnover (%)	86.79	71.43	75.86	77.14	79.82	105.30	85.58	80.07
Annual Expense Ratio (%)	1.20	0.87	0.95	1.16	1.21	1.28	1.30	1.14
Fund Age (years)	14.85	22.99	22.35	19.07	12.91	11.32	13.29	16.75
Number of Stocks Held, Mean	113	60	74	86	112	114	125	162
Number of Stocks Held, Median	66	50	58	56	70	72	77	77

This table provides summary statistics for the sample of actively managed U.S. equity mutual funds in the Thomson Financial/CDA holdings and CRSP fund returns data. The sample period is from 1982 to 2011. Fund TNA, annual returns, turnover, the expense ratio, and fund age are obtained from the CRSP. Fund age is the number of years since the fund's organization. Data on the 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 five-year snapshots.

2.2. Stock data and definition of anomaly characteristics

All stock characteristics except dispersion in analysts' forecasts are constructed using the CRSP and Compustat datasets. Dispersion in analysts' forecasts is based on data from the Institutional Brokers Estimate System (I/B/E/S). The monthly returns and prices for common stocks (CRSP SHRCD 10 or 11) traded on the New York Stock Exchange, American Stock Exchange, and NASDAQ are from the 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 obtained from reports with fiscal year-ends in year $t-1$. We use a six-month gap to allow for possible late submissions 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 are obtained from the most recent quarterly earnings report and are used for the next 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. The daily and monthly risk-free rate, the Fama–French (Fama and French, 1993) three-factors, and the Carhart (1997) momentum factor are obtained from Kenneth French's website.[5]

The 15 considered characteristics are divided into six groups. The classical group consists of size (S), the book to market (B/M), and momentum (MOM). These three characteristics underlie Carhart (1997) four-factor model. Investment variables capture firm capital investment. This group consists of total asset growth (AG), abnormal capital investments (CI), and the investments-to-assets ratio (I/A). Financing characteristics measure firm stock issuance activity with net stock issues (NSI) and composite stock issuance (CSI). Two accounting anomalies capture firm earnings management and balance sheet manipulation with accruals (ACC) and net operating assets (NOA), respectively. Measures of firm performance such as return on assets (ROA) and standardized unexpected earnings (SUE) belong to the profitability group. Idiosyncratic volatility (IVOL), Ohlson's O-score (OSC), and dispersion in analysts' forecasts (DISP) are grouped together, since they broadly quantify uncertainty about a firm. The detailed definition of each characteristic is provided in the online Appendix.

3. Stock mispricing measure

3.1. Measure of anomalies' implied mispricing

This section aims to develop a measure of the implied mispricing of anomalies in an attempt to separate likely undervalued stocks from overvalued stocks. Although each individual anomaly could itself be a proxy for mispricing, we believe that it would be a noisy one. To increase the precision of the proxy for mispricing, we attempt to diversify away some of the noise in each individual anomaly by aggregating information embedded in each measure of the anomaly.

To this end, we modify the binary score approach of Piotroski (2000) and Mohanram (2005) by constructing a ternary signal for the 15 individual anomaly characteristics. Piotroski (2000) constructs a binary F-score to search for value firms based on financial statements. Similarly, Mohanram (2005) constructs a binary G-score to differentiate high-quality from low-quality growth firms. The scoring approach of Piotroski (2000) and Mohanram (2005) is based on the sum of nine (eight) binary fundamental signals, with a score range of zero to nine (eight). On the other hand, our measure of anomalies' implied mispricing is constructed as the sum of 15 anomalies' implied ternary signals, where each signal has three possible scores: long (+1), neutral (0), and short (–1).

In detail, for each stock j and anomaly characteristic k at the end of June of year t, the signal $S_{k,j,t}$ is one if the stock's anomaly characteristic at the end of June of year t is in the long leg (highest-performing 30%). On the other hand, the signal $S_{k,j,t}$ is -1 if the stock's anomaly characteristic at the end of June of year t is in the short leg (lowest-performing 30%). If the stock's anomaly

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

characteristic is in the neutral leg (mid-performing 40%) or is missing at the end of June of year *t*, the signal $S_{k,j,t}$ is zero. The assumption implicit in the construction of this signal is that each of the characteristics-based strategies has a mispricing effect. Thus, if a stock is likely undervalued (overvalued) 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 year *t* is defined as sum of the above ternary signals:

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

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

where the indexes *j* and *k* indicate the stock and anomalies considered, respectively. In other words, the A-score is defined as the number of undervaluation signals of stock *j* minus the number of overvaluation signals of stock *j* out of the 15 anomaly characteristics. The A-score has an intuitive interpretation. Since the A-score is composed of the individual anomaly signals, by definition, the A-score ranges from –15 to 15. Thus, a positive (high) A-score means that the stock is more likely to be undervalued and a negative (low) A-score indicates that the stock is more likely to be overvalued. For example, if a stock's A-score is six, the stock is undervalued by at least six signals. Based on the definition of the A-score, we hypothesize that (1) stocks with a high A-score (undervalued stocks) will exhibit superior future performance, on average, and (2) funds that have stocks with a higher A-score (undervalued stocks) will exhibit superior performance, on average, relative to funds that have stocks with a lower A-score (overvalued stocks).

3.2. Average returns of anomalies' implied mispricing-based portfolios

This section investigates the cross-sectional relation between the A-score and subsequent returns of the 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 the 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 $t + 1$.

Table 2 presents the average value-weighted returns and stock characteristics for the deciles based on the A-score. Panel A reveals that the returns of the decile portfolios increase monotonically with the A-score. For example, the average annual return is 8.21% for the lowest A-score decile portfolio (P1) and monotonically increases to 15.97% for the highest A-score decile portfolio (P10). The return spread between P10 and P1 (P10 − P1) is significantly positive, at 7.76% ($t = 2.14$). The three-factor alpha of the return spread between P10 and P1 is also significantly positive. This spread is larger than the spread of an individual anomaly-based strategy, indicating that our A-score measure captures cross-sectional mispricing in the stock market well. The table further shows that the alpha of the bottom two A-score deciles (P1 to P2) is significantly negative; hence, we refer to these stocks as overvalued. 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 undervalued.

The analysis is repeated in Panel B of Table 2 on a subset of stocks held by the mutual funds. Specifically, at the end of June each year, we include stocks held by at least one fund in our sample. We refer to this sample as stocks held by mutual funds. From 1982 to 2011, this sample contains 71,308 firm–year observations. The results for the mutual fund holdings analysis exhibit similar patterns. The three-factor alpha of long-short portfolio (P10-P1) is 10.04% and it is statistically significant.

Table 2 also reports the average size, market beta, and return volatility for each stock decile. Generally, the A-score of stocks is positively related to size and inversely related to the market beta, return volatility, and idiosyncratic volatility (IVOL). The results imply that undervalued stocks are larger and exhibit lower systematic, total, and idiosyncratic risk. Finally, the results for the mutual fund holdings analysis reveal similar patterns. Compared to stocks in the stock universe, those held by mutual funds have greater market capitalization and lower return volatility, consistent with the findings of prior studies (e.g., Lakonishok, Shleifer, & Vishny, 1992; Del Guercio, 1996; Gompers & Metrick, 2001).[6]

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 undervalued stocks. In the next section, we examine whether this is indeed the case.

[6] We include size, book-to-market, and past returns to construct a composite measure of mispricing. However, our construction of A-score may not be appropriate in that we use the Fama-French three-factor model and the Carhart four-factor model to calculate abnormal returns of portfolios constructed on the A-score ranking. To investigate this issue, we replicate Table 2 with 12 characteristics by excluding size, book-to-market, and past returns. We find that the empirical results are qualitatively similar, and results are available upon request.

Table 2
Returns and characteristics across A-score–sorted stock deciles.

	Panel A: Stock Universe							Panel B: Stocks Held by Mutual Funds						
Decile Portfolio	A-Score	Return (%)	Alpha (%)	Size ($ millions)	Market Beta	Volatility (%)	Ivol (%)	A-Score	Return (%)	Alpha (%)	Size ($ millions)	Market Beta	Volatility (%)	Ivol (%)
P1	−6.84	8.21	−6.55	829	1.36	27.07	41.90	−6.79	10.50	−5.18	958	1.31	25.43	38.67
		(1.80)	(−3.87)						(2.24)	(−2.92)				
P2	−4.14	9.21	−5.07	999	1.26	22.87	29.23	−4.08	10.05	−5.30	1193	1.26	22.89	29.76
		(2.20)	(−3.24)						(2.25)	(−3.29)				
P3	−2.64	11.09	−2.99	1192	1.18	20.92	27.59	−2.61	13.03	−2.04	1513	1.17	21.02	29.65
		(2.76)	(−1.77)						(3.24)	(−1.00)				
P4	−1.46	13.64	0.86	1337	1.08	19.05	25.06	−1.45	14.99	1.69	1614	1.05	18.41	24.97
		(4.15)	(0.63)						(4.60)	(1.21)				
P5	−0.41	13.14	0.53	1427	1.03	17.42	21.59	−0.43	14.06	0.49	1673	1.05	17.62	22.34
		(3.99)	(0.48)						(3.98)	(0.34)				
P6	0.60	12.97	0.68	1633	1.01	17.19	21.15	0.59	13.50	0.34	2035	1.05	17.62	21.09
		(4.05)	(0.70)						(3.74)	(0.28)				
P7	1.68	13.37	1.91	1949	0.94	16.10	22.31	1.70	14.19	2.33	2578	0.92	15.85	23.77
		(4.66)	(1.92)						(5.17)	(2.05)				
P8	2.77	14.45	2.11	1846	0.98	16.08	19.93	2.79	14.53	1.65	2482	0.98	16.17	20.32
		(5.19)	(1.97)						(5.07)	(1.39)				
P9	4.02	13.46	2.45	2309	0.89	14.97	19.71	4.01	13.95	2.54	3065	0.90	15.19	19.17
		(4.42)	(3.12)						(4.54)	(2.80)				
P10	6.17	15.97	5.12	2812	0.80	13.64	20.57	6.18	16.37	4.86	3466	0.83	14.02	20.71
		(6.00)	(4.85)						(5.92)	(3.80)				
P10 – P1		7.76	11.68						5.86	10.04				
		(2.14)	(5.11)						(1.49)	(4.08)				

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

4. Do mutual funds hold stocks based on mispricing measures?

4.1. Construction of a fund investing measure

Given the evidence of the anomalies' implied mispricing in the stock market, an investor could argue that mutual funds should aggressively hold likely undervalued 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 overweight undervalued stocks and underweight overvalued stocks compared to the benchmark. In contrast, if mutual funds trade on the opposite side of cross-sectional mispricing, we expect that mutual funds overweight overvalued stocks and underweight undervalued stocks compared to the benchmark. We thus 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 et al. (1995) and (Ali et al., 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 one to 10, with decile 1 (10) representing the most overvalued (undervalued) stocks. Given a fund's holdings, we calculate the weighted average of the fund's A-score rankings. The fund investing measure is the weighted average of the A-score decile rank of stocks held by the fund:

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

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*, and $w_{i,j,t}$ is the value of stock *j* owned by fund *i* as a percentage of the total value of stocks the fund holds at the end of June of year *t*:

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

with $n_{i,j,t}$ as the number of shares of stock *j* held by the fund and $p_{j,t}$ as the market price of stock *j* at the end of June of year *t*. A high investing measure value indicates that the fund tilts its holdings toward undervalued 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 a passive benchmark portfolio. We use the S&P 500 index as a benchmark because it is the most widely used in the literature. For a 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 compare funds; so, in our second exercise, we calculate the investing measure for an individual fund.

This approach can be extended to any characteristic-ranking variable. We extend the procedure by applying it to 15 individual anomalies and calculate each portfolio's characteristic score. For example, a fund's '*BM score'* is the weighted average book-to-market decile rank of stocks held by the fund. To make the relation between the characteristic score and the direction of mispricing consistent in all the characteristics considered, the characteristic ranking is set from one to 10, with decile 1 (10) representing the lowest-performing (highest-performing) 10% of stocks 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 stock market mispricing?

This section presents the empirical evidence for the fund investing measure. We start with a comparison of investment styles 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.

Panel A of Table 3 reports the average portfolio investing measure for the funds, the S&P 500 index, and the CRSP market index. First, focusing on the individual characteristic score of funds and benchmarks, the results show that the characteristic scores for ME, AG, CI, IA, NS, CSI, ACC, NOA, and DISP for the funds are significantly higher than the S&P 500 index or the CRSP market index. On the other hand, for BM, MOM, SUE, and ROA, the funds have a significantly lower characteristic score than the benchmarks. For IVOL and OSC, the differences in scores depend on the choice of benchmark: the IVOL and OSC scores are lower than the S&P 500 index but higher than the CRSP market index. This result suggests 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 a firm's book to market, momentum, profitability, or uncertainty.

While each anomaly is itself a mispricing measure, each individual anomaly could be a noisy measure of the mispricing. Fortunately, our investing measure diversifies away some of the noise in each individual anomaly and thereby increases the precision of the mispricing. In addition, use of 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. In the aggregate, mutual funds tend to hold more overvalued stocks than those in the S&P 500 index or the CRSP market index. The result suggests that mutual funds do not invest in the anomalies' implied mispricing, on average.

Table 3
Portfolio characteristics of average mutual fund.

Panel A: Average Fund Portfolio Characteristics

	Funds	CRSP Stocks	S&P 500	Funds – CRSP		Funds – S&P 500	
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&P 500	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&P 500	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)

This table presents the mean values of the portfolio investing measure, the portfolio characteristic scores of individual anomalies, and the portfolio weights across A-score–sorted stock deciles from June 1982 to June 2011. The funds column indicates the fund portfolio in the aggregate, where we pool the equity holdings of all funds into a single portfolio. For the fund portfolio, a stock's weight is the percentage of the portfolio value invested in the stock. The CRSP stocks columns refers to a portfolio of all common stocks in the CRSP database with non-missing A-scores, computed using CRSP, Compustat, and I/B/E/S data. The S&P 500 column refers to a portfolio of S&P 500 stocks. For the stock portfolio, capitalization weight is used as a stock's weight. Panel A reports the time-series averages for the characteristics of each portfolio. Panel B reports the weights in each stock A-score decile for each portfolio. The numbers in parentheses are *t*-statistics.

We further examine the distribution of the portfolio weight of each stock decile ranked by A-scores. 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 reports the means of these portfolio weights. For comparison, we also report the portfolio weights of the S&P 500 index and the CRSP market index. Consistent with the results using the investing measure, we find that mutual funds tend to underweight undervalued stocks and overweight overvalued stocks compared to the benchmark. Relative to the S&P 500 index, the funds significantly overweight stocks in the three lowest A-score deciles and significantly underweight stocks in the two highest A-score deciles. For instance, the portfolio weights of the funds on stocks in the most undervalued decile (P10) are 5.10% lower and the portfolio weights of the funds on stocks in the most overvalued decile (P1) are 3.76% higher than for the S&P 500 index.

Our evidence suggests that mutual funds have adverse allocation effects on stock market mispricing. In addition, this adverse allocation to anomalies' implied mispricing could be one reason why, on average, mutual funds do not generate significant profit, since 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 et al., 2016; Akbas et al., 2015).

Although mutual funds, on average, do not trade on the anomalies' implied mispricing, it is possible that a subset of funds do. To determine this, we compute the 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 those most actively following the anomalies' implied mispricing strategy.

Table 4 reports the means of portfolio weights in each A-score–sorted stock decile for investing measure–sorted fund deciles. We find that the top three investing measure decile (D8, D9 and D10) funds correctly allocate their portfolio regarding anomalies' implied mispricing; in other words, they overweight undervalued stocks (P8 to P10) and underweight overvalued stocks (P1 to P3) relative to the those of the CRSP market index. In particular, D10 funds significantly overweight stocks in the three highest A-score deciles (P8 to P10) and significantly underweight stocks in the three lowest A-score deciles (P1 to P3). The results indicate that a subgroup of mutual funds trade on the anomalies' implied mispricing. However, a large number of funds hold stocks with the opposite side of the anomalies' implied mispricing. The seven bottom investing measure decile (D1 to D7) funds adversely allocate their portfolio regarding anomalies' implied mispricing. Furthermore, D1 funds greatly overweight overvalued stocks (P1 to P3)

Table 4
Portfolio weights of investing measure–sorted fund deciles across A-score–sorted stock deciles.

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)

This table shows the portfolio weights in each A-score–sorted stock decile for investing measure–sorted fund deciles from June 1982 to June 2011. Decile D1 has the lowest investing measure funds and D10 the highest. The 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 portfolio divided by the total value of the portfolio. We also report the difference in portfolio weights between the D1 (D10) fund and CRSP market portfolios.

relative to the CRSP market index. These results suggest that, given prevailing mispricing in the stock market, a substantial number of mutual funds cannot exploit the mispricing.

5. Performance analysis

Given the anomalies' implied strategy generates superior risk-adjusted performance, the primary question in this Section is whether investing measure has an explanatory power for the cross-section of mutual fund returns. We hypothesize cross-sectional differences in fund performance: Funds that hold greater proportions of stocks with a higher A-score (undervalued stocks) will exhibit overperformance relative to funds that hold stocks with a lower A-score (overvalued stocks). In other words, the higher a fund's investing measure, the higher its average performance.

5.1. Fund performance across investing measure–sorted portfolios

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

$$R_t - RF_t = \alpha + \beta_1 MKTRF_t + \beta_2 SMB_t + \beta_3 HML_t + \varepsilon_t \quad (5)$$

$$R_t - RF_t = \alpha + \beta_1 MKTRF_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 UMD_t + \varepsilon_t \quad (6)$$

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 the risk-free rate; and SMB_t, HML_t, and UMD_t are the 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.

Table 5 reports the average annual performance across investing measure–sorted fund deciles. Each June of year *t*, we sort funds into investing measure deciles. We compute the equal-weighted performance within each of the 10 fund portfolios over the entire sample period.

Some features of Table 5 are worth highlighting. First, empirical result in Table 5 shows underperformance of mutual funds, on average. For the full sample, the annualized three-factor alpha and the annualized four-factor alpha after fees are −1.08% and −1.10%. More importantly, we find that the overall underperformance is related with our investing measure: The average investing measure for all deciles is less than that of S&P index or the CRSP market index. In sum, our empirical finding indicates that mutual funds do not invest in the anomalies' implied mispricing, on average, and our investing measure indeed helps understand the underperformance of mutual funds.

Second, empirical finding in Table 5 suggests that investing measure has an explanatory power for the cross-section of mutual

Table 5
Fund performance across investing measure–sorted fund deciles.

Fund Decile	Investing measure	Fund Performance before Fees					Fund Performance after Fees				
		Raw Return	3-Factor Alpha	4-Factor Alpha	Sharpe Ratio	Vola-tility	Raw Return	3-Factor Alpha	4-Factor Alpha	Sharpe Ratio	Vola-tility
D1	3.32	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	3.66	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	3.83	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	3.87	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	4.28	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	4.54	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	4.80	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	5.10	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	5.43	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	6.08	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	4.50	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	2.76	0.46	1.91	1.55			0.67	2.12	1.56		
		(0.34)	(2.14)	(1.81)			(0.49)	(2.38)	(1.75)		

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

fund returns. For performance after fees, funds with the lowest-investing measure underperform their benchmarks by 2.23% per year (t = –3.08) and the loss further holds at 1.77% ($t = -2.44$) under the four-factor model. The evidence indicates that funds with the lowest investing measure do the worst in terms of net return destroying value for fund investors. Relatedly, the investing measure does improve fund performance. Funds with the highest-investing measure exhibit economically significant positive alphas before fees. For D10 funds, the annualized before-fee three- and four-factor alphas are 0.97% (t = 2.07) and 0.87% (t = 1.83), respectively. However, the risk-adjusted returns after fees indicate that the highest-investing measure funds essentially match their benchmark returns. This empirical finding could be explained by the work of Berk and van Binsbergen (2015), who show that fund managers capture the rents of their outperformance by charging higher fees.

Finally, Table 5 shows that both Sharpe ratios demonstrate a fairly monotonic positive relation with the mutual fund investing measure. The gross Sharpe ratio increases from 0.42 to 0.58 and the net Sharpe ratio increases from 0.36 to 0.51. The difference in returns between the top and bottom deciles 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 portfolios toward undervalued stocks can help mutual funds improve their mean–variance efficiency by increasing their Sharpe ratio and lowering their total risk.[7]

Further, we investigate whether the relation between investing measure and fund performance varies across investment objectives. Note that from the Thomson Financial data, we include all funds with a reported investment objective code (IOC) of aggressive growth (2), growth (3), growth and income (4), and unclassified (9). Therefore, we replicate Table 5 for subgroups of aggressive growth, growth, and growth and income, and Table 6 presents our empirical finding. Panel A shows fund performance of aggressive growth funds, and Panel B reveals the results for growth funds. Panel C displays fund performance for growth and income funds.[8]

[7] One may argue that our empirical findings are sensitive to the choice of anomaly variables considered. To address this issue, we replicate Table 5 with subsets of the 15 anomaly variables. Note that the 15 anomalies constituting A-score can be classified into 6 categories as described in Section 2. To calculate A-score more simply and parsimoniously, we calculate A-score using two alternative sets of anomalies. Those sets include only single representative anomaly in each category except for the classical group. The first set includes anomaly variables of abnormal capital investment, composite stock issue, net operating asset, standardized unexpected earnings, dispersion in analysts' forecasts, and all variables in classical group. The second set consists of asset growth, net sock issue, accruals, return on assets, idiosyncratic volatility, and all variables in classical group. Regardless of subsets of anomalies considered, the patterns of fund performance are qualitatively similar to the result in Table 5. For the sake of simplicity, we do not report empirical results, and our empirical finding is available upon request.

[8] For each Panel, we only report the values of D1 and D10 portfolios to save the space. The entire results are available upon request.

Table 6
Fund performance across different investment objectives.

Fund Decile	Investing measure	Fund Performance before Fees Raw Return	3-Factor Alpha	4-Factor Alpha	Sharpe Ratio	Vola-tility	Fund Performance after Fees Raw Return	3-Factor Alpha	4-Factor Alpha	Sharpe Ratio	Vola-tility
Panel A: Aggressive growth funds											
D1	2.52	10.09	−2.80	−3.05	0.18	19.55	8.59	−4.30	−4.55	0.15	19.55
		(3.83)	(−1.35)	(−1.47)	(3.73)		(3.26)	(−2.10)	(−2.23)	(3.32)	
D10	5.79	15.84	3.29	2.69	0.26	16.58	14.47	1.92	1.32	0.23	16.58
		(6.04)	(3.38)	(2.64)	(5.44)		(5.54)	(1.93)	(1.34)	(5.04)	
D10 - D1	3.28	5.75	6.09	5.74			5.88	6.22	5.87		
		(2.66)	(2.12)	(2.30)			(2.73)	(2.17)	(2.36)		
Panel B: Growth funds											
D1	2.23	12.45	−0.20	−0.66	0.22	16.50	11.10	−1.54	−2.00	0.19	16.49
		(4.95)	(−0.31)	(−0.83)	(5.17)		(4.35)	(−2.62)	(−2.64)	(4.69)	
D10	6.21	13.19	1.44	0.95	0.26	13.32	11.99	0.25	−0.25	0.23	13.32
		(4.70)	(3.06)	(2.27)	(4.47)		(4.25)	(0.52)	(−0.60)	(4.05)	
D10 - D1	3.98	0.74	1.64	1.61			0.88	1.78	1.75		
		(0.77)	(1.63)	(1.70)			(0.94)	(1.84)	(1.92)		
Panel C: Growth and income funds											
D1	2.76	12.24	0.11	−0.46	0.25	13.30	11.03	−1.11	−1.68	0.22	13.30
		(4.83)	(0.32)	(−0.74)	(5.08)		(4.34)	(−3.33)	(−2.73)	(4.63)	
D10	6.57	12.08	1.72	1.62	0.27	11.10	10.94	0.58	0.48	0.24	11.10
		(4.80)	(2.59)	(2.44)	(5.62)		(4.32)	(0.86)	(0.72)	(5.07)	
D10 - D1	3.81	−0.16	1.61	2.08			−0.09	1.68	2.16		
		(−0.31)	(2.43)	(2.75)			(−0.16)	(2.49)	(2.79)		

This table presents the mean values of the fund performance measure for various investment objectives 1982 to 2011. Panel A shows fund performance of aggressive growth funds, and Panel B reveals the results for growth funds. Panel C displays fund performance for growth and income funds. For each June of year *t*, we rank mutual funds with the same investment objective code into deciles based on their investing measure. Decile D1 has funds with the lowest investing measure and D10 has funds with the highest investing measure. The fund performance measures are the raw return, the Fama–French (Fama and French, 1993) three-factor alpha, the Carhart (1997) four-factor alpha, and the Sharpe ratio, both before and after fund expenses. We also report the volatility for each fund decile. Heteroscedasticity-adjusted *t*-statistics are in parentheses.

Among investment objectives considered, we find that investing measure generates huge return differences among funds with aggressive growth. For the two risk-adjusted performance measures—the three- and four-factor alphas—the differences between the highest and lowest investing measure deciles after fees are significantly positive: 6.22% ($t = 2.17$) and 5.87% ($t = 2.36$), respectively. In addition, among funds with aggressive growth, funds in D10 generate abnormal after-fee returns. Note that investment objective of aggressive funds is "maximum capital appreciation", and therefore often bear greater risk than other funds. Since we find that our A-score well captures mispricing of individual stocks, the large return spreads among aggressive funds seem natural. In addition, for funds with growth and growth and income, investing measures are positively related with fund returns although the return spreads become narrower.

5.2. Regression analysis

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

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

The list of explanatory variables includes the investing measure, fund size measured by the logarithm of fund TNA, fund age, the expense ratio, turnover ratios measured by the minimum of the aggregated sales or the aggregated purchases of securities divided by the fund's average 12-month TNA, prior risk-adjusted returns, and prior flows. We also control for other predictors of future fund performance known from the literature, such as active shares, tracking errors, and *R*-squared values. Cremers and Petajisto (2009) show that active share,[9] the fraction of the fund's portfolio that deviates from the benchmark index, is a proxy for stock selection. They find that funds with a high active share outperform funds with a low active share. The authors also employ tracking error, the 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 skill. In addition, Amihud and Goyenko (2013) show that *R*-squared, obtained from a regression of a fund's return on a multifactor benchmark model, is a measure of selectivity. They find that lower *R*-squared values imply greater stock selection skill. We estimate Eq. (7) with robust estimators of variance clustered at the fund level.

Table 7 shows the estimation results for the panel regression, which controls for mutual fund characteristics and other predictors.

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

Table 7
Regression analysis of fund performance.

	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)
$(\log(\text{TNA}))^2$		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-Squared			−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

This table presents regression evidence of the predictability of performance based on the fund investing measure, calculated for each June of year t. The fund performance measures are the Fama–French (Fama and 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 include a number of fund characteristic control variables all as of June of year t. Here, log TNA is the natural log of TN and log age is the natural log of the number of years since the fund was first offered, plus one. The expense ratio is the ratio of the total investment that shareholders pay for the fund's operating expenses. The turnover ratio is the minimum of the aggregated sales or the aggregated purchase of securities, divided by the fund's 12-month TNA. Past performance is the fund's performance measured from July of year $t - 1$ to June of year t. Flow is the sum of the previous four quarters' flow, where the quarterly flow is measured 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. The active share is computed according to Petajisto (2013). The tracking error is computed as the standard deviation of the difference between monthly fund returns and benchmark index returns, measured from July of year $t - 1$ to June of year t. The R-squared term is obtained from Carhart's four-factor model with a 24-month estimation period. All specifications include year dummies. The regressions are estimated using a robust estimator of the variance clustered at the fund level. The numbers in parentheses are t-statistics.

When the control variables are not included in the regression, the coefficient of the investing measure is significantly positive for all versions of alpha (i.e., three- and four-factor models) calculated with gross and net fund returns. When a fund's investing measure 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 the investing measure remains when other variables are added. For example, a one-unit increase of the investing measure raises 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 differs from that contained in other skill measures. Overall, our empirical results indicate that mutual funds that tend to hold undervalued stocks have higher risk-adjusted performance.

Altogether, the results in Table 7 demonstrate predictability of the fund investing measure for fund performance. Risk-adjusted performance is greater for funds with a higher investing measure. This means that mutual funds that slant their portfolios toward undervalued stocks earn higher risk-adjusted returns, even after considering transaction costs and management fees.

6. Further analysis of the fund investing measure

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

6.1. *Determinants of the fund investing measure*

We perform a cross-sectional analysis of fund characteristics across the investing measure. Panel A of Table 8 reports the average

Table 8
Determinants of the fund investing measure.

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-Squared (%)	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 the 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)	

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

fund characteristics of each investing measure–sorted fund decile. We compare several characteristics of mutual funds across investing measure deciles: TNA, the expense ratio, the turnover ratio, fund age, flow, the number of stocks held, the market beta, cash holdings, and other skill measures. All characteristics are measured at the end of June of each year *t*, the same time the fund investing measure is calculated. To see the relation between the investing measure and other fund characteristics, we also run the following pooled panel regressions of the fund investing measure on fund characteristics, with Panel B reporting the estimation results:

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

Several patterns are worth mentioning. First, TNA and the number of stocks held by a fund exhibit an inverted-U shaped pattern, which indicates that D10 funds have a similar size and level of diversification as D1 funds. Smaller funds are able to pursue more active trading strategies because their trading causes less of a price impact than larger funds do (e.g., Pástor, Stambaugh, & 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 the definition of the investing measure, this result is consistent with other studies.

Second, funds that adversely allocate to mispricing charge higher expense ratios than funds that 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 (Gil-Bazo & 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 indicates that agency problems could play a role in explaining the portfolio composition opposite to anomalies' implied mispricing. The adverse allocation of funds in D1 could be caused by the ill-motivated trades of agency-prone fund managers.

Third, funds with a lower investing measure are younger than funds with a higher investing measure, on average. The positive relation between fund age and investing measure indicates 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 8 shows that, if we refer to prior studies, the lowest investing measure funds (D1) exhibit high managerial skill. Funds that tilt their portfolio toward overpriced stock have the highest active share, the highest tracking error, and the lowest *R*-squared values. However, unlike previous studies, we fail to show that funds with a high active share, a high tracking error, and a low *R*-squared value have superior returns. One possible reason is that our investing measure is not linearly related to other skill measures, as shown in Panel B. Thus, the information contained in our investing measure differs from that in the other measures. One limitation of the aforementioned skill measures is that they are calculated only based on 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 mispricing. Thus, it is likely that D1 funds are extremely deviated from their benchmark due to 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 the fund investing measure

It is possible for a fund to have a high investing measure due to chance instead of deliberate trading. If a money manager deliberately maintains a portfolio toward undervalued stocks, we observe persistence in the fund investing measure over time. We therefore calculate the transition probabilities for D1 and D10 funds over the subsequent five years. Table 9 reports the results.

We find that funds with D1 and D10 are highly persistent for both short and long horizons. Funds in extreme deciles are more likely to remain in the same extreme deciles than to move to the middle or another extreme decile. After one year, 55.9% and 54.5% of the D10 and D1 funds remain in the same decile, respectively. This tendency still holds for longer horizons. More than one-third of the funds in deciles 1 and 10 remain in these deciles, even after five years. The persistence in the investing measure indicates persistence in trading strategies, suggesting that funds deliberately tilt their portfolio toward stocks with either a low or high A-score.

7. Potential explanations

We find that funds that tilt their portfolios toward undervalued stocks earn higher risk-adjusted returns. However, we have shown that, in the aggregate, mutual funds hold stocks with a direction adverse to stock market mispricing with strong persistence. These two findings raise a fundamental question: why do professional money managers tilt their portfolios toward overpriced stocks? By reviewing the related literature, we think that this question can be answered with the managers' agency problem.

Karceski (2002) develops an agency model in which active fund managers tilt their portfolios toward high-beta stocks. Fund managers select stocks to maximize their funds' expected assets under management because they are compensated by management fees, which are proportional to the assets under management. Mutual fund investors chase returns through time; in particular, there are large aggregate inflows into mutual funds after market runups (Warther, 1995). Mutual fund investors also chase returns across funds, so the highest-performing funds obtain the largest inflows (Sirri & Tufano, 1998). The interaction of these two

Table 9
Transition matrix for D1 and D10 funds.

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
					D1 Funds					
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					
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

This table presents the percentage of D1 (D10) funds that 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 deciles based on the investing measure, where the investing measure is the weighted average of the A-score decile ranks of individual stocks held by the mutual fund. Decile D1 has the lowest investing measure funds and D10 the highest. The sample period is 1982–2011.

Table 10
Regression analysis of agency costs.

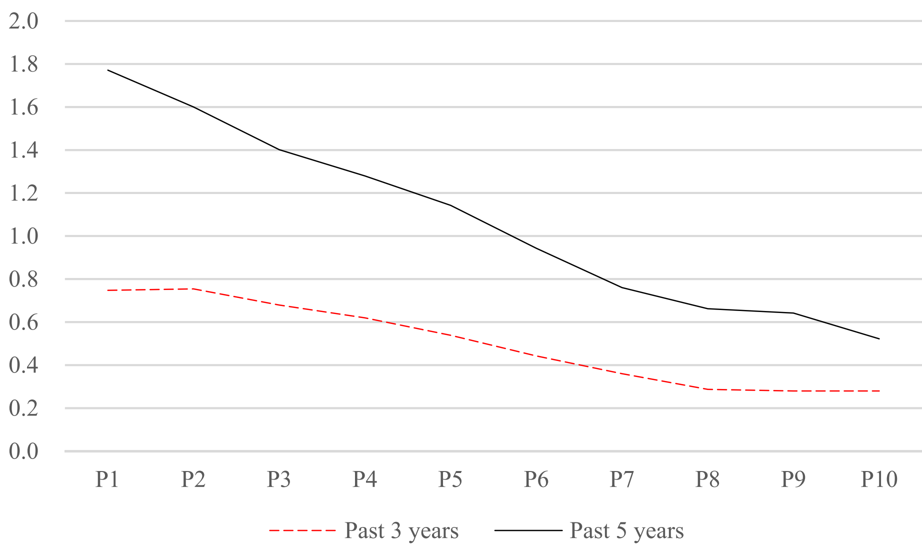
Dependent variable	Expense Ratio			Return Gap		
Investing Measure	−0.0444	−0.0192	−0.0121	−0.8853	−0.8159	−0.5439
	(−7.44)	(−2.43)	(−1.67)	(−5.47)	(−3.38)	(−2.80)
log(TNA)	−0.1007	−0.0863	−0.1033	−0.3716	−0.2519	−0.4995
	(−4.67)	(−3.85)	(−4.60)	(−0.97)	(−0.45)	(−0.99)
$(\log(TNA))^2$	0.0019	0.0024	0.0033	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
	(−2.30)	(−4.30)	(−3.09)	(−0.62)	(−1.16)	(0.20)
Expense Ratio				−0.2613	−0.8371	−0.7603
				(−0.87)	(−1.39)	(−1.33)
Turnover Ratio	0.0007	0.0009	0.0011	−0.0134	−0.0238	−0.0179
	(4.15)	(2.76)	(2.49)	(−5.02)	(−4.41)	(−3.91)
Flow	0.0001	0.0002	0.0001	−0.0034	−0.0053	−0.0030
	(0.84)	(1.59)	(0.45)	(−0.90)	(−0.98)	(−0.65)
Performance	0.0000	−0.0012	−0.0024	−0.0277	−0.0408	0.1479
	(−0.14)	(−3.62)	(−3.89)	(−1.64)	(−1.66)	(5.09)
Return Volatility	0.0020	0.0009	−0.0012	−0.1237	−0.1679	0.0164
	(6.04)	(1.85)	(−1.70)	(−8.87)	(−8.74)	(0.55)
Cash Holdings			−0.0003			−0.0071
			(−0.35)			(−0.18)
Market Beta			0.1449			−2.7503
			(3.96)			(−1.92)
Active Share		0.0049	0.0055		0.0929	0.0544
		(7.37)	(7.26)		(4.94)	(3.28)
Tracking Error		0.0080	0.0109		−0.1968	−0.2524
		(3.76)	(3.26)		(−1.74)	(−2.20)
RSQ		−0.0025	−0.0037		−0.0696	−0.0346
		(−2.47)	(−3.19)		(−2.10)	(−0.80)
Adj R^2	19.58	28.33	32.06	17.76	22.42	17.66
N	25,100	12,354	8,905	22,585	11,529	8,258

This table presents the results for the regression of agency costs. We use two proxies for agency costs: the expense ratio and the return gap. All specifications include year dummies. The regressions are estimated using robust estimators of variance clustered at the fund level. The numbers in parentheses are *t*-statistics.

flow–performance relations shows that fund managers hold stocks that outperform during bull markets to maximize their management fees. Since high-beta stocks tend to outperform in up markets, active fund managers tilt their portfolios toward high-beta stocks. Because overpriced (low A-score) stocks have a high market beta, the fact that many funds tilt their portfolios toward overpriced stocks is potentially explained by this agency model of fund managers. To apply the above argument, we investigate whether our investing measure is related to the agency costs of funds. Our testable hypothesis is as follows:

H1: All else being equal, funds with a lower investing measure have higher agency costs.

Panel A: Average Past Cumulative Returns across A-Score Stock Deciles



Panel B: Time Series of Cumulative Returns for P1 and P10

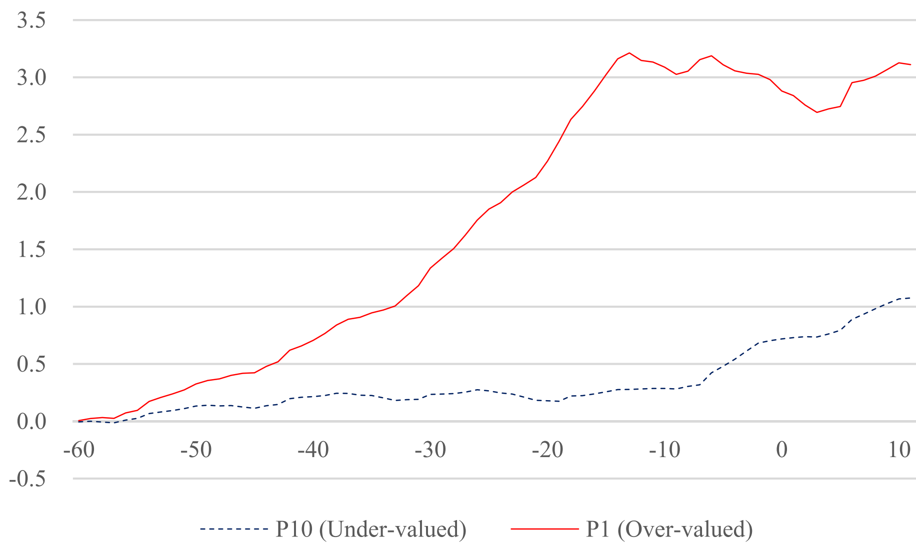


Fig. 1. Long-term past cumulative returns of overpriced stocks. This figure shows the average long-term past cumulative returns of each A-score–sorted stock decile from June 1982 to June 2011. Panel A shows the average three-, and five-year past cumulative returns for each A-score stock decile. Panel B shows the past 60-months' time-series cumulative returns of the P1 and P10 deciles. Time 0 refers to the formation date of the A-score–sorted stock deciles.

Unfortunately, we have no direct observable measures for the agency costs. So, we examine proxies of agency costs within 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 the value of fund investors. This suggests that fees play a role in the agency conflict between the fund manager and fund investors. Studies including those of Del Guercio, Dann, and Partch (Guercio et al., 2003), Bogle (2005), Friesen and Sapp (2007), Gil-Bazo and Ruiz-Verdu (2009) and Ferris and Yan (2009) suggest that fund fees capture the agency costs of funds. Our second measure of agency costs is return gaps. Kacperczyk, Sialm, and Zheng (2008) show that the return gap, 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. The authors suggest that a fund's opaqueness could proxy for agency problems and opaque funds tend to exhibit large return gaps. Therefore, we use return gaps as a proxy for agency costs, where a large return gap is an indicator of high agency costs.

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

$$Agency\ Costs_{i,t} = \beta_1 Investing\ Measure_{i,t} + Controls + Year\ Dummies + \varepsilon_{i,t} \tag{9}$$

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

Overall, our empirical findings from previous sections could be caused by the ill-motivated trades of agency-prone fund managers. Due to the agency problem, they could tilt toward overpriced stocks, characterized by a high beta, consistent with Karceski (2002) model. However, our empirical results should be interpreted with caution since our measures are not perfect proxies for agency costs.

Finally, we conjecture that overvalued stocks typically have a favorable history of past returns and hence could appear to be a safer choice as far as managers' personal career risks are concerned.

Panel A of Fig. 1 displays the average long-term past cumulative returns of each A-score stock decile and Panel B shows the past 60-months' time series cumulative returns of the P1 and P10 deciles. The results in Fig. 1 indicate that overpriced stocks exhibit a favorable track record of past returns. Overpriced stocks are the past five years' and the past three years' winners. Thus, career-concerned managers have motivation to choose overpriced stocks.

8. Conclusion

We study whether actively managed equity mutual funds exploit the stock market mispricing implied by 15 well-known pricing anomalies. Although the literature extensively documents cross-sectional anomalies in expected equity returns, it does not explicitly examine mutual funds from this perspective. We define the mispricing of a stock using A-scores, which are the composite of 15 pricing anomalies. Furthermore, to quantify how actively a fund follows the anomalies' implied mispricing strategy, we create a fund investing measure.

Our empirical evidence shows that mutual funds, on average, do not follow anomalies' implied mispricing. There is a tendency for the majority of mutual funds to overweight overvalued stocks. This adverse allocation to anomalies' implied mispricing could be one reason why, on average, mutual funds cannot beat the market, since the anomalies' implied strategy generates superior risk-adjusted performance. We also show that the fund investing measure has cross-sectional predictive power for future fund performance. This finding implies that our investing measure is an alternative predictor of future fund returns. We further propose rationales for why mutual funds do not exploit the stock market mispricing. We find that the agency problem of managers are related to fund manager behavior.

Our results have implications for the growing debate on portfolio delegation. Generally, fund investors delegate their investments to fund managers in the hope that they will benefit from the managers' skills. However, our results raise the possibility that most mutual fund managers cannot beat the market due to agency problem of fund managers.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.najef.2020.101189.

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