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Do Institutional Investors Exploit Market Anomalies? New Evidence from Alternative Mutual Funds

Xin Gao
Sacred Heart University, gaox3@sacredheart.edu

Ying-Chih Wang

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Abstract

This paper investigates the anomaly trading behavior of a sample of mutual funds mimicking hedge fund strategies, namely alternative mutual funds (AMFs), based on both of their long and short equity positions. We document that AMFs trade on anomalies by buying underpriced stocks and short-selling overpriced peers. While AMFs' buys and sells based on their long positions do not generate superior performance, their short-selling and covering activity based on their short positions significantly negatively predicts future abnormal returns. However, this predictability is mainly attributed to size and the nine anomaly characteristics considered. Overall, the results suggest that AMFs are sophisticated investors and that their short positions are more informative relative to their long positions.

Keywords: Alternative mutual funds, market anomaly, long/short positions, short sell, sophisticated investor.

1 Introduction

Whether institutional investors can exploit stock market anomalies is a question of long-standing interest to academics. While institutional investors are generally perceived to be sophisticated, there is mixed evidence on whether they can exploit the cross-sectional predictability of stock returns. For instance, Lewellen (2011) shows that institutions fail to tilt their portfolios to take advantage of the well-known stock return anomalies. Edelen, Ince, and Kadlec (2016) further document that institutions as a whole trade against anomalies and thus contribute to cross-sectional mispricing. However, Akbas, Armstrong, Sorescu, and Subrahmanyam (2015) suggest that while mutual funds appear to exacerbate mispricing, hedge funds tend to correct it. The latter result is confirmed by Calluzzo, Moneta, and Topaloglu (2017) who examine the long side of hedge fund trades.

It is worth noting that previous studies have examined the trading behavior of institutional investors mostly based on their long-side portfolio holdings due to data availability. Mutual funds typically undertake long-only positions. Although hedge funds can freely use various alternative strategies involving a combination of leverage and long/short positions, their short positions are not publicly available because they are generally not registered with the U.S. Securities and Exchange Commission (SEC) and thus are exempt from the disclosure regulations to which more traditional institutional investors (such as mutual funds) must adhere.

The focus of the existing literature on institutional investors' long positions, however, likely understates their ability to exploit market anomalies, given that asset pricing theories have long established that overpricing should be more prevalent than underpricing due to limits to arbitrage. For instance, Miller (1977) argues that asset prices should reflect the views of optimists rather than those of pessimists due to impediments to short sales. Consistent with this view, the empirical studies document that market anomalies derive their profitability mainly from selling short overpriced stocks rather than buying underpriced ones [e.g., Stambaugh, Yu, and Yuan (2012, 2015); Avramov, Chordia, Jostova, and Philipov (2013)].

In this paper, we provide new empirical evidence to shed light on the long-standing debate over whether institutional investors can exploit market anomalies by investigating the anomaly trading behavior of a sample of so-called alternative mutual funds (AMFs henceforth, also commonly referred to as hedged mutual funds), based on both of their long and short equity positions. Unlike traditional long-only mutual funds, AMFs can use hedge-fund-like strategies such as short selling. However, unlike hedge funds, they are still subject to the same regulations as traditional mutual funds and thus are required by the SEC to report complete portfolio holdings (including short positions) on a regular basis.

We focus on AMFs for several reasons. First and foremost, given the availability of their short positions, AMFs provide a unique setting to study the anomaly trading skills of institutional investors. As discussed previously, market anomalies extract their profitability mainly from short-selling overpriced stocks [e.g., Stambaugh et al. (2012, 2015); Avramov et al. (2013)]. As a result, short positions are likely to provide additional insignts into the investors' anomaly trading ability, which otherwise would not have been captured by long positions alone.

Second, AMFs have played an increasingly important role in the field of investment management in recent years. According to Investment Company Institute 2017 Fact Book, the total number of AMFs has increased from 181 to 478 over the period of 2007-2016; the total assets under management by AMFs have also increased from $42 billion to $213 billion during this period. It is believed that the AMF sector will continue to grow because AMFs "provide access to hedge-fund-like strategies with the fee structure, liquidity, and regulatory requirements of mutual funds" [Agarwal, Boyson, and Naik (2009), p.g. 274]. Our research aims to investigate the sources of performance for AMFs and see if they can explore potential market mispricing on the long as well as the short side.

Finally, Agarwal et al. (2009) show that about half of AMFs have managers with hedge fund experience. Therefore, it is not unreasonable to argue that one could infer hedge funds' trading strategies from AMFs' trading behavior, to the extent that managers manage AMFs and hedge funds in a similar way. The short positions of AMFs are particularly informative considering that the same positions of hedge funds are typically undisclosed trading secrets.

We mainly address three questions in this paper: (1) Can AMFs exploit the cross-sectional predictability of stock returns? (2) Does their anomaly trading predict future abnormal returns? (3) Is the predictability due to AMFs' ability to interpret public information or their possession of private information? Note that our analysis centers around the sophisticated investor hypothesis (SIH). Under the SIH, if AMFs are sophisticated investors, we expect them to buy underpriced stocks and short-sell overpriced ones. In addition, the SIH asserts that AMFs' trades should be non-negatively related to future anomaly returns. However, the SIH does not require that AMFs possess private information.

Using a sample of 415 equity-focused AMFs from Morningstar during 2002–2016, we first examine whether AMFs trade according to anomaly prescriptions based on their long and short equity positions separately. We measure AMFs' trading activity mainly by changes in the fraction of AMFs with outstanding long or short positions in a given stock over a six-quarter trading window prior to the anomaly portfolio formation date. Consistent with the SIH, the results show that AMFs as a whole tend to trade in the "right" direction implied by stock market anomalies.

Specifically, the average fund exhibits a propensity to buy (short sell) underpriced (overpriced) stocks based on the nine anomalies considered in the paper. Our findings are contrary to those of prior studies that institutional investors trade on the "wrong" side of anomalies and that mutual funds' trades exacerbate stock market anomalies [Edelen et al. (2016); Akbas et al. (2015)].

We next investigate whether AMFs' anomaly trading leads to positive future abnormal returns. The results indicate that AMFs as a group seem to earn positive abnormal returns from their buys in underpriced stocks, which, however, are at least partially offset by negative abnormal returns generated from the overpriced stocks they buy. Therefore, based on their long equity positions, we do not find compelling evidence that AMFs' buys and sells are related to superior abnormal returns. In contrast, anomaly stocks sold short by AMFs underperform those they cover for both the underpriced and overpriced groups across all individual anomalies. On average, the difference in Fama and French (1993) three-factor alpha between the stocks sold short and covered by AMFs is -4.37% (-4.96%) annually for the underpriced (overpriced) group with a t-statistic of -2.09 (-2.53). Thus, based on their short positions, we again document evidence supportive of the SIH that AMFs in aggregate earn significantly positive abnormal returns in anomaly stocks they short-sell and cover. These results suggest that short positions are more informative than long positions. Therefore, previous studies that only focus on the long positions of institutional investors are likely to understate their anomaly trading ability.

Finally, we show that the change in the fraction of AMFs with long positions in a stock has negative predictive power for future stock returns, but this predictability is largely driven by the funds' preferences for large cap stocks. More importantly, we document the change in the fraction of AMFs with short positions also significantly negatively predicts future stock returns, indicating that the increasing number of AMFs that short-sell a stock signals lower future returns. However, this predictability can be attributed to size and the nine anomaly characteristics considered, suggesting that AMFs' short selling and covering activity do not contain additional private information beyond what is contained in those characteristics.

Our paper contributes to the literature in several aspects. First, we provide new insights into the literature as to whether institutional investors can take advantage of market anomalies. Existing research provides mixed evidence on whether traditional mutual funds can exploit individual stock market anomalies, such as momentum [Grinblatt, Titman, and Wermers (1995)], accrual [Ali, Chen, Yao, and Yu (2008)], and post earnings announcement drift [Ali, Chen, Yao, and Yu (2009)]. Several recent studies [e.g., Lewellen (2011) and Edelen et al. (2016)] show that institutional investors as a whole (mutual funds in particular) indeed trade against well-known stock anomalies. Akbas et al. (2015) and Calluzzo et al. (2017) show that hedge funds can instead correct mispricing. Unlike previous studies that investigate the anomaly trading behavior of institutional investors only based on their long positions, we are the first to examine both of the long and short positions of a subgroup of institutional investors, namely AMFs, and show that they can trade on market anomalies not only by buying underpriced stocks, but more importantly, also by short-selling overpriced stocks.

This paper is also part of the growing literature on the performance of AMFs. Agarwal et al. (2009) show that AMFs outperform traditional mutual funds and underperform hedge funds. Chen, Desai, and Krishnamurthy (2013) show that mutual funds that use short sales generate abnormal returns from their long and short positions. Huang and Wang (2013) document that AMFs provide values to investors especially during financial crisis and their short positions generate alpha. Our paper supplements prior studies by providing further evidence that anomaly trading could be one of the primary sources of performance for AMFs. Specifically, we document that AMFs' short-selling and covering activity predicts future abnormal returns, and this predictability is mainly attributed to size and the nine anomaly characteristics considered.

Finally, our study is closely related to the literature on short selling. Several studies have examined short sellers' trading on anomalies. For instance, Hwang and Liu (2014) study which market anomalies short arbitragers might prefer. Wu and Zhang (2015) examine how the anomaly trading behavior of short sellers has changed over time. While these studies focus on short sellers in general, we focus on a particular group of institutional investors that use short sales, namely AMFs, and examine how they trade on anomalies based on both of their long and short positions.

The rest of the paper proceeds as follows. Section 2 describes the data and variables used. Section 3 presents our main empirical findings on the anomaly trading behavior of AMFs and its return predictability. Section 4 provides several robustness tests. We conclude in Section 5.

2 Data and variable definitions

2.1 Data

We collect data from several sources in this paper. First, our data on AMFs are obtained from Morningstar, which provides holdings and characteristics information for both live and defunct funds. Unlike the Thomson database that only reports mutual funds' long positions in U.S. domestic equities, Morningstar provides both long and short equity positions, and thus enables us to study both the long and short sides of mutual fund trading. Note that most previous studies on the trading behavior of mutual funds or other institutional investors, particularly those related to stock market anomalies, focus on the long side exclusively.

We also obtain the data on stock returns, market capitalization, trading volume, and other stock characteristics from the Center for Research in Security Prices (CRSP), and the accounting data used to construct stock market anomaly variables from Compustat annual and quarterly files. Following the conventions in the literature, we include all common stocks (CRSP share code of 10 or 11) traded on NYSE, Amex, and NASDAQ, and then exclude financials (CRSP SICCD between 6000 and 6999), utilities (CRSP SICCD between 4000 and 4999), and stocks with prices under $5. We also adjust monthly stock returns for delistings to avoid survivorship bias, following Shumway (1997). Finally, we download monthly series of market, size, value, and momentum factors and the risk-free rates from Kenneth French's online data library.[1]

To construct our sample of AMFs, we start with all mutual funds that are classified as Alternative under Morningstar Category Group. The initial sample contains 893 unique AMFs. We further keep only the funds that are identified as Long-short Equity, Market Neutral, Multialternatve, 130–30, and Bear Market under Morningstar Category. According to Morningstar Category Classifications, funds in the five categories are likely to trade on U.S. equities, which we confirm in the data.[2] This gives us a refined sample of equity-based AMFs, for which we collect data on quarterly holdings and fund characteristics over the period from 1984Q1 to 2016Q4 from Morningstar. Lastly, we merge the sample funds' domestic equity holdings with the stock data obtained from the CRSP/Compustat database using CUSIPs and tickers.

Overall, our final sample includes 415 AMFs, among which 410 (319) have long (short) positions in U.S. domestic stocks. The funds trade a total of 5947 unique stocks during the sample period, of which 5785 (4273) are held long (sold short). Fig. 1 plots the numbers of funds and

[1]Kenneth French's data library: `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`.

[2]The Morningstar category methodology documentation is available at `http://advisor.morningstar.com/Enterprise/VTC/MorningstarCategoryClassificationEffectiveApril2017.pdf`.

stocks held over time. From Panel A, we can see that the total number of funds increases from 2 in 1984 to 230 in 2016. The vast majority of the funds hold long positions in U.S. equities, whereas about 77% (319) of the sample funds have short positions. Panel B depicts the number of stocks held in the aggregate portfolio of AMFs. The total number of traded stocks increases from 52 to 2000 during the sample period. The dashed red line shows that the funds barely hold any short positions prior to 2002. From 2002 to 2016, the number of shorted stocks rises from 203 to 1668. As the sample contains few funds and almost no short holdings before 2002Q1, we use the period from 2002Q1 to 2016Q4 as the main sample for our analysis.

2.2 Variable definitions

We define the variables used in our analysis in this subsection. Stambaugh et al. (2012) examine eleven well-documented stock market anomalies and classify them into nine categories. To avoid redundancy, we employ one anomaly from each of the nine categories. The nine anomalies studied in our paper are defined as follows.

1. Total accruals (ACC) – the change in net working capital minus depreciation scaled by average total assets for the previous two fiscal years [Sloan (1996)].

2. Asset growth (AG) – the growth rate of firm's total assets in the previous fiscal year [Cooper, Gulen, and Schill (2008)].

3. Gross profitability (GP) – gross profits divided by total assets [Novy-Marx (2013)].

4. Investment to assets (ITA) – the change in gross property, plant, and equipment plus changes in inventory scaled by lagged total assets [Lyandres, Sun, and Zhang (2007)].

5. Momentum (MOM) – the continuously compounded return from month t-13 to month t-2 [Jegadeesh and Titman (1993)].[3]

6. Net operating assets (NOA) – the difference between operating assets and operating liabilities divided by total assets in the previous fiscal year [Hirshleifer, Hou, Teoh, and Zhang (2004)].

7. Net stock issuance (NSI) – the natural log of one plus the growth rate of split-adjusted shares outstanding in the previous fiscal year [Pontiff and Woodgate (2008); Fama and French (2008)].

8. Ohlson O-score (OSC) – the probability of bankruptcy in a static model using accounting variables, such as net income divided by assets, working capital divided by market assets, and current liability divided by current assets [Ohlson (1980)].

9. Return on asset (ROA) – the income before extraordinary items divided by one-quarter-lagged total assets [Chen, Novy-Marx, and Zhang (2011); Fama and French (2006); Wang and Yu (2013)].

Note that six out of the nine anomalies, ACC, AG, GP, ITA, NOA, and NSI, are updated annually due to the availability of accounting data. For these anomalies, we form value-weighted anomaly portfolios at the end of June each year and hold the portfolios for 12 months, from July of year t to June of year t+1. The remaining three anomalies, MOM, OSC, and ROA, are updated every quarter using the Compustat quarterly files and then held for a quarter. To ensure the accounting data are publicly available, we skip one quarter when forming value-weighted anomaly portfolios for OSC and ROA.

We next define trading measures. As our main interest is in AMFs' trading behavior in stock market anomalies, we focus on how the funds as a group adjust their long and short positions

[3] We skip month t-1 to control for potential short-term reversal [see, e.g., Jegadeesh (1990); Lehmann (1990)].

separately in anomaly stocks as the characteristics of the underlying stocks vary over time. We consider two measures of trading. The first (and primary) measure is defined as the change in number of AMFs with an outstanding long or short position in a given stock divided by the average number of AMFs holding stocks in the same market capitalization decile as of the beginning of the trading window. For brevity, we refer to this measure as the change in fraction of AMFs and label it as Δ%Fund, henceforth. This measure is similar to the change in ownership breadth in Chen, Hong, and Stein (2002). The second measure is the change in the fraction of a company's outstanding shares held long or sold short by AMFs. We call this trading measure the change in fraction of shares and label it as Δ%Shr. We employ Δ%Fund as our main trading measure for two reasons. First, unlike Δ%Shr, Δ%Fund is immune to the large trades of a few funds as it places equal weight on each fund. Second, Δ%Fund only tracks initiated and closed positions in a stock, which may better reflect the funds' active and most recent investment ideas and thus are more likely to be motivated by the managers' opinions on mispricing in the underlying stocks. In contrast, Δ%Shr tracks changes in existing positions in a stock as well. Such trades tend to be less informative about the future performance of the underlying stocks, because a fund could passively increase or decrease existing positions in its holding stocks in response to cash inflows or outflows [see, e.g., Coval and Stafford (2007); Lou (2012)]. We consider the six-, four-, two-, and one-quarter trading windows prior to the anomaly portfolio formation date. Following Edelen et al. (2016), we adopt the six-quarter trading window, which covers the realization of anomaly ranking variables and ends three months after the full public disclosure of annual 10-k, as the primary one in this paper. The results based on the other windows are similar in direction.

3 Empirical results

We present our main empirical findings in this section. First, we report the properties of the nine stock market anomalies studied in the paper. We then discuss the characteristics of our sample AMFs as well as the stocks held long and sold short by these funds. Next, we present the main results on AMFs' trading activity in anomalies and their anomaly trading performance. We also explore AMFs' trading preferences for stocks characteristics other than the nine anomaly characteristics. Finally, we investigate the predictive ability of AMFs' trading activity for future stock returns.

3.1 Properties of stock market anomalies

In this subsection, we examine the properties of the nine stock market anomalies studied in this paper. Following Stambaugh et al. (2012), we sort stocks into ten decile portfolios based on each of the nine anomalies, with decile 10 (1) being the best- (worst-) performing decile. We then compute value-weighted average returns for each decile portfolio in any given month.

Panel A of Table 1 presents, for each anomaly, annualized three-factor alphas (in percentage) of the long, short, and long-short portfolio strategies, respectively, using all stocks with non-missing anomaly characteristics in the CRSP universe over the period of 1984 to 2016. The long (short) leg refers to the best- (worst-) performing decile portfolio and the long-short portfolio is the long minus the short leg. The last column (AVG) refers to a combination strategy that takes equal positions across the nine anomaly portfolios.

Several patterns emerge from the table. First, consistent with the findings documented in previous studies (e.g., Stambaugh et al. (2012)), the alphas of the long-short portfolio strategies across the nine anomalies are all positive and statistically significant, with an average of 6.98% per year (t-statistic=5.04). Second, the abnormal returns on the long-short strategies appear to be largely derived from stocks in the short legs. Averaged across the nine anomalies, the short leg generates an annualized alpha of -4.59%, whereas the long leg captures 2.40%. The evidence suggests that short-selling overpriced anomaly stocks in the short legs is more profitable than buying the underpriced in the long legs, in the absence of shorting costs. This asymmetric pattern is also consistent with the findings reported in Stambaugh et al. (2012).

In Panel B of Table 1, we repeat the analysis using a subset of stocks held by AMFs during the same sample period. The results exhibit similar patterns: all long-short portfolio strategies generate positive three-factor alphas with an average of 5.44% per year (t-statistic=4.30) and the magnitude of the short alpha is larger than that of the long alpha (3.28% vs. 2.16%). Interestingly, the average alpha across the nine long-short portfolios (5.44%) based on stocks held by AMFs is smaller than that (6.98%) based on the CRSP stocks. A closer examination shows that the difference is mainly attributed to the difference in the short alphas. Overall, the results indicate that compared with the CRSP sample, the subset of stocks held by AMFs appears to be less mispriced.

Panel C of Table 1 presents pair-wise correlations among the long-short benchmark-adjusted returns of the nine anomalies. We follow Stambaugh et al. (2012) to compute the benchmark-adjusted returns as the sum of the intercept and the residuals from the regression of a long-short strategy's monthly excess returns on the Fama and French (1993) three factors. The general observation is that the anomalies are not strongly related to each other. The pair-wise correlation coefficients range from -0.17 to 0.41, with an average of 0.15 across the nine anomalies (t-statistic=1.07). The correlation results suggest that the anomaly characteristics are relatively distinct from each other and that our results on AMFs' trading on particular anomalies are less likely driven by their trading on other anomalies.

3.2 Characteristics of alternative mutual funds and stocks held

We describe the characteristics of AMFs in our sample and the stocks held by these funds during our main sample period of 2002–2016 in this subsection. Panel A of Table 2 provides summary statistics of fund characteristics, including total net assets (TNA), fund age, turnover ratio, and expense ratio. Our sample AMFs have an average TNA of $245.38 million with a standard deviation of $623.17 million. The sample tends to be skewed towards small funds, as evidenced by a median TNA of $41 million. These funds are relatively young with an average age of 6.7 years. The mean (median) turnover ratio is 297.83% (182.47%), indicating that these funds are highly actively managed. The average annual expense ratio of the sample funds is 1.95% per year (median=1.90%), which appears to be higher than that of traditional mutual funds (1.30%).

We next compare the characteristics of stocks held by AMFs with those of a benchmark portfolio. As AMFs hold both long and short stock positions, we sort all stocks held into two portfolios: the long portfolio that contains stocks with outstanding long positions, and the short portfolio including stocks with outstanding short positions. For the purpose of comparison, we also construct a benchmark portfolio (labelled as "the CRSP portfolio") using all stocks with non-missing characteristics in the CRSP database. Following Chen, Jegadeesh, and Wermers (2000), we calculate the characteristic rank score for each stock as the stock's decile rank on the characteristic relative to all stocks in the CRSP portfolio, with decile 10 (1) being the best- (worst-) performing stocks. Thus, the portfolio-level characteristic rank score is the market-capitalization weighted average rank score of all stocks held in the portfolio. Note that despite the rank score for a stock is calculated at the end of June each year for annually updated anomalies and at the end of each quarter for quarterly updated anomalies, the portfolio rank scores are computed each quarter based on quarterly holdings.

Panel B of Table 2 reports the rank scores on 11 stock characteristics (book-to-market ratio (BM), size, and the nine anomalies studied in our paper) as well as an average score (labelled as "AVG") across the 11 characteristics for the long, short, and CRSP portfolios, respectively. Comparing the characteristic rank scores of the long and CRSP portfolios (Column "(2)-(1)"), we show that the long portfolio has higher rank scores than the CRSP portfolio for all characteristics except AG, BM, and SIZE. On average, the difference between these two portfolios is 0.15 (t-statistic=9.80), indicating that AMFs as a group tend to hold long positions in underpriced (i.e., better performing) anomaly stocks. From the comparison between the short and CRSP portfolios (Column "(3)-(1)"), we can see that the differences in rank scores are significantly negative for AG, BM, ITA, MOM, ROA, and SIZE. For ACC, GP, NOA, NSI, and OSC, the differences are marginally positive and statistically insignificant. The short portfolio has an average rank score that is 0.12 lower than the benchmark portfolio, suggesting that AMFs tend to short overpriced anomaly stocks. Finally, the comparison between the long and short portfolios (Column "(2)-(3)") shows that the rank scores of the long portfolio are all significantly higher than those of the short portfolio except for AG and SIZE, with an average difference of 0.28 (t-statistic=11.22). Overall, the results suggest that, on average, AMFs as a whole have a propensity to hold long (short) positions in under- (over-) priced anomaly stocks. In other words, AMFs exhibit preferences for stock characteristics in a way that follows anomaly prescriptions.[4]

[4]Note that the characteristic rank score is calculated based on the levels of holdings, which reflect AMFs' persistent demand for stocks with certain characteristics, rather than the changes in holdings, which more accurately measure AMFs' trading activity. Our paper focuses more on the latter.

3.3 Anomaly trading

In this subsection, we explore whether AMFs trade on the nine stock market anomalies. Recall that we split stocks held by AMFs into the long and short portfolios based on their outstanding positions. Within each portfolio, we compute, for a given stock, the annualized change in the fraction of funds with outstanding positions in the stock (Δ%Fund) and the annualized change in the fraction of shares held (Δ%Shr) during the anomaly portfolio formation window. We then separately examine AMF's trading activity based on their long and short portfolios. The sign of the trading variable implies the direction of trade. For stocks in the long portfolio, Δ%Fund>0 (Δ%Fund<0) indicates buying (selling) activity; for stocks in the short portfolio, Δ%Fund>0 (Δ%Fund<0) is a sign of short-selling (covering). Δ%Shr shares the same implications.

Table 3 presents the results on AMFs' trading activity across the nine anomalies. For each anomaly, we classify the stocks held by all sample funds into underpriced, neutral, and overpriced groups. The underpriced (overpriced) group contains the 30% best- (worst-) performing stocks related to the anomaly, and the neutral group includes the middle 40% stocks.[5] The neutral group serves as a benchmark for evaluating AMFs' trading on overpriced and underpriced stocks. We report the average fund's buying/selling and short-selling/covering activities in each of the three groups based on AMFs' long and short equity positions in Panels A and B, respectively. In both panels, we also compute the fund's average trading activity across the nine anomalies in the last set of columns labelled as "AVG". In the rest of this section, our discussion focuses on our main trading variable – the change in the fraction of funds (Δ%Fund) based on a trading window of six quarters prior to the anomaly portfolio formation date.[6]

[5] In unreported results, we also consider an alternative classification based on 20%-60%-20% and find qualitatively similar results.

[6] The results based on the trading window of one, two, or four quarters are similar. Also note that the results based

We first discuss the results based on AMF's long equity positions. If AMFs are sophisticated investors, they are expected to exhibit the ability to exploit anomaly-implied mispricing by buying underpriced stocks, i.e., the stocks in the long leg of an anomaly. Thus, one would expect to observe a higher (lower) level of buying activity in the underpriced (overpriced) group, relative to the neutral group.

The results in Panel A of Table 3 appear to support this prediction: for all of the nine anomalies, with the exception of AG, GP, and NSI, the increases in Δ%Fund for stocks in the underpriced (overpriced) group are significantly greater (less) than in the neutral group. On average, the difference in Δ%Fund between the underpriced (overpriced) and neutral portfolios is 4.19% (-4.06%) with a t-statistic of 4.33 (-4.36). The results suggest that based on their long equity positions, AMFs in aggregate tend to trade on stocks following anomaly predictions. It is worth noting that our sample funds seem to trade extensively on momentum. For example, the difference in Δ%Fund between the underpriced and overpriced groups is 27.15%, which is substantially greater than the average of 8.24% across the nine anomalies. This result is consistent with institutional investors' return chasing behavior documented in the literature [Grinblatt et al. (1995); Wermers (1999); Badrinath and Wahal (2002); Sias, Starks, and Titman (2006); Sias (2007)].

We then present the results based on AMFs' short equity positions. Unlike traditional mutual funds, AMFs could also take advantage of the mispricing by short-selling overpriced stocks, i.e., the stocks in the short leg of an anomaly. It is well documented in the literature that the short positions in the short-leg anomaly portfolio are more profitable than the long positions in the long leg (See, e.g., Stambaugh et al. (2012)). Therefore, if AMFs as a group intend to trade on anomalies, particularly by short-selling the overpriced stocks, one should observe relatively

on the change in fraction of shares (Δ%Shr) are similar, particularly in the case of AMF's short equity positions.

higher (lower) short-selling activity in the overpriced (underpriced) group as compared to the neutral group.

The evidence in Panel B of Table 3 is largely in support of this prediction. First, we note that the changes in the fraction of funds (Δ%Fund) are all positive across the nine anomalies, indicating the increasing number of funds short-selling the stocks over the sample period. Second, comparing the changes across the three stock groups, we can see that the increases in Δ%Fund for stocks in the overpriced group are greater than the increases in the neutral group for all the nine anomalies by an average of 8.34% (t-statistic=8.15). This result indicates that AMFs have stronger intention to short-sell overpriced stocks implied by anomalies relative to the neutral peers. Third, the difference in Δ%Fund between the underpriced and neutral groups, averaged across the nine anomalies, is 1.41% (t-statistic=-3.17), which is also consistent with anomaly prescriptions. Last, the comparison between the underpriced and overpriced groups indicates that the levels of short-selling activity in underpriced stocks are all economically and statistically significantly lower than the levels in overpriced stocks, with an average difference of -9.76% (t-statistic=-7.89). Overall, the results based on AMFs' short equity positions suggest that AMFs appear to exhibit strong interests in short-selling the overpriced stocks implied by stock market anomalies.

In summary, the results show that consistent with the sophisticated investor hypothesis, AMFs as a whole tend to trade in the "right" direction implied by stock market anomalies. Specifically, the average fund exhibits a propensity to buy underpriced stocks and short-sell overpriced peers. Our findings are contrary to those of prior studies that institutional investors trade on the "wrong side" of anomalies and that mutual funds' trades exacerbate stock market anomalies [Frazzini and Lamont (2008); Akbas et al. (2015)]. It is, however, worth pointing out that our findings are based on AMFs – a subgroup of institutional investors who can adopt hedge-fund-like strategies such as short selling while being subject to the same regulations as traditional mutual funds, which differ from the samples examined in other studies, such as traditional mutual funds or institutional investors in general.

3.4 Anomaly trading performance

In this subsection, we explore whether AMFs' anomaly trading leads to future positive abnormal returns. Again we sort stocks held by AMFs into the long and short portfolios based on their outstanding positions. Within each portfolio, we further sort stocks into sub-portfolios based on anomaly characteristics and Δ%Fund. Specifically, on each anomaly portfolio formation date, we rank stocks into sub-portfolios by the anomaly variable: the underpriced (overpriced) group which contains the top (bottom) 30% best- (worst-) performing stocks, and the neutral one which includes the middle 40% stocks. We also sort stocks into quintile portfolios based on Δ%Fund over the six quarters prior to the anomaly portfolio formation date. Note that we refer to the top (bottom) 20% of Δ%Fund as buy (sell) for the long portfolio and as short-sell (cover) for the short portfolio. For both the long and short portfolios, we then form four value-weighted anomaly portfolios conditional on AMFs' trading by taking the intersection of the underpriced and overpriced groups for each anomaly with the top and bottom quintiles of Δ%Fund.

Table 4 reports the annualized three-factor alphas of each of the four conditional anomaly portfolios as well as the differences in alphas between the top and bottom Δ%Fund quintiles, i.e., Buy – Sell and Short-sell – Cover, for stocks held long and sold short by AMFs, respectively, in Panels A and B. In each panel, we report the results for each of the nine anomalies. We also form four aggregate conditional anomaly portfolios that take equal-weighted positions across the nine anomalies and report their performance in the last section (AVG). According to the sophisticated investor hypothesis, one would expect to observe a positive relation between AMFs' trades and future anomaly returns. In other words, based on AMF's long (short) stock positions, anomaly stocks that AMFs buy (short-sell) should outperform (underperform) those they sell (cover).

We first focus on the results for the long portfolio in Panel A of Table 4. Across the nine anomalies, the stocks AMFs buy outperform those they sell for five out of the nine anomalies in both the underpriced and overpriced groups. However, only among the underpriced stocks implied by NOA is the difference in alphas statistically significant (t=1.98). On average, AMFs in aggregate earn an abnormal return of 3.15% per year (t-statistic=1.96) from the anomaly-implied underpriced stocks they buy. Meanwhile, they also sell stocks classified as underpriced, which generate an average annual alpha of 2.37% (t-statistic=1.55). The spread in alpha is therefore not statistically different from zero. Turning to the overpriced group, we can see that AMFs' aggregate trades are somewhat value-destroying: the overpriced stocks they buy on average earn an annual alpha of -1.31%, though statistically insignificant. Overall, the results indicate that AMFs as a group seem to earn positive abnormal returns from their buys in underpriced stocks. However, the returns are partially offset by negative abnormal returns generated from the overpriced stocks they buy. Therefore, we do not find compelling evidence that AMFs' buys and sells are related to superior abnormal returns based on their long stock positions.

We next discuss the results for the short portfolio in Panel B of Table 4. The table shows that anomaly stocks sold short by AMFs underperform those they cover for both the underpriced and overpriced groups across all of the nine anomalies, with the exception of the overpriced group implied by GP. On average, the spreads in three-factor alpha between the stocks sold short and those covered by AMFs are economically large and statistically significant: -4.37% (-4.96%) annually for the underpriced (overpriced) group with a t-statistic of -2.09 (-2.53). The results suggest that based on their short stock positions, AMFs in aggregate earn significantly positive abnormal returns in anomaly stocks they short sell and cover.

Overall, in sharp contrast to the results for the long portfolio, those based on the short portfolio provide strong support for the sophisticated investor hypothesis. In particular, the evidence indicates that while AMFs' buys and sells do not earn abnormal anomaly returns, their short-selling and covering activity appear to generate superior future abnormal anomaly returns.

3.5 Characteristics of conditional anomaly portfolios

To shed further light on the trading behavior of AMFs, we explore whether AMFs as a whole exhibit other trading preferences besides the nine anomaly characteristics studied in this paper. Specifically, we examine five characteristics for the four conditional anomaly portfolios within each of the long and short portfolios as constructed in the previous subsection: the number of constituent stocks (%NSTOCKS), market capitalization (MKTCAP), book-to-market (BM), turnover (TURN), and idiosyncratic volatility (IVOL).

Table 5 reports the mean values across the nine anomalies for each of the five characteristics based on stocks held long and sold short by AMFs in Panels A and B, respectively. The first set of columns (%NSTOCKS) shows the average number of stocks in each portfolio divided by the total number of stocks included in all four portfolios. From Panel A, based on their long stock positions, AMFs exhibit significantly higher buying activity than selling for both underpriced and overpriced stocks, although the difference is much larger for underpriced stocks compared to overpriced ones (16.57% vs. 4.87%). Based on stocks with short positions in Panel B, we can see that, within the underpriced group, the number of stocks sold short by AMFs does not differ significantly from the number of stocks covered. In contrast, for the overpriced group, the stocks AMFs short sell are significantly more than those they cover (34.56% vs. 18.30%), indicating more intensive short-selling activity of overpriced stocks implied by the anomalies.

The second set of columns (MKTCAP) summarizes the average market capitalization of constituent stocks of the four conditional anomaly portfolios. Panel A shows that, based on their long positions, AMFs clearly have a strong preference to buy large cap stocks and to sell small cap ones. The differences in MKTCAP between stocks bought and sold by AMFs are economically large and statistically significant for both underpriced and overpriced groups. This result is in line with the preference for large cap stocks that has been found in mutual funds and institutional investors in general [Falkenstein (1996); Gompers and Metrick (2001); Yan and Zhang (2007)]. Based on their short positions (Panel B), AMFs show a propensity to short-sell small cap stocks and to cover large cap stocks, particularly in the overpriced group.

The third set of columns (BM) shows the average book-to-market ratios. Based on their long stock positions (Panel A), AMFs do not seem to take into account BM particularly in buying and selling underpriced stocks. This result differs from previous finding that institutional investors show a strong preference for high BM stocks [See, e.g., Gompers and Metrick (2001)]. On the other hand, Panel B shows that the stocks sold short in both overpriced and underpriced groups, on average, have a significantly lower BM than those they cover, suggesting that AMFs have a systematic preference to short-sell low BM (i.e., growth) stocks and to cover those with high BM (i.e., value stocks).

The fourth set of columns (TURN) presents the average monthly turnover ratios. In Panel

A, we do not find any significant difference in turnover between the Buy and Sell portfolios for the underpriced group. This result indicates that AMFs do not seem to account for underlying stock liquidity in buying and selling underpriced stocks, while institutional investors, short-term in particular, have a strong preference for turnover [Yan and Zhang (2007)]. However, as shown in Panel B, the average turnover values of the Short-sell portfolios are significantly higher than those of the Cover portfolios for both underpriced and overpriced groups, implying that stock liquidity seems to play an important role in AMFs' short-selling and covering decisions.

In the last set of columns (IVOL), we report the average idiosyncratic volatility for the four conditional anomaly portfolios. Based on their short position (Panel B), AMFs show a strong tendency to short-sell (cover) stocks with high (low) idiosyncratic volatility. However, based on their long positions (Panel A), we do not find such preference in their buying and selling activity.

To summarize, based on their short stock positions, we find strong evidence that AMFs in aggregate exhibit significant propensity to short sell overpriced, small cap, low book-to-market, high turnover, and high idiosyncratic volatility stocks. In contrast, based on their long stock positions, there is little evidence that the funds have preferences for book-to-market, turnover, or idiosyncratic volatility, especially in their buys and sells of underpriced stocks.

3.6 Alternative mutual funds' trading and future stock returns

In this subsection, we investigate the relation between AMFs' trading and future stock returns. In general, previous studies has documented a positive relation between the levels of and changes in institutional ownership and future stock returns at the short horizon and attribute the source of the predictability to an informational advantage [e.g., Gompers and Metrick (2001); Yan and

Zhang (2007)]. On the contrary, Edelen et al. (2016) find a significant negative long-horizon relation between institutional trading and future stock returns.

Following this line of research, we explore whether AMFs' trading activity predicts future stock returns. Specifically, we conduct Fama-MacBeth regressions of future monthly stock excess returns on Δ%Fund over the six-, four-, two- or one-quarter trading window prior to the anomaly portfolio formation date, controlling for firm size (SIZE), book-to-market ratio (BM), and the nine anomaly characteristics. [7]

Table 6 reports Fama-MacBeth regression results for all stocks held long and sold short by AMFs, respectively, in Panels A and B. We first regress monthly stock excess returns on Δ%Fund in Columns (1)–(4). According to the sophisticated investor hypothesis, if AMFs' trading predicts future returns, we would expect the coefficients on Δ%Fund to be significantly positive (negative) for long (shorted) stocks. From Panel A , however, we find no evidence of predictability for long stocks. The coefficients on Δ%Fund across the four trading windows are all negative and statistically significant for six and four quarters, indicating the negative predictive power of AMFs' buying and selling. This result is indeed consistent with the findings of Edelen et al. (2016). In contrast, Panel B shows that Δ%Fund is negatively related to future stock returns for shorted stocks, statistically significantly for the six- and one-quarter trading window, indicating that the increasing number of funds that short a stock signals lower future returns. This result is consistent with the prediction of sophisticated investor hypothesis.

To further investigate the sources of the predictability, we add SIZE and BM to the regressions in Columns (5)–(8). Focusing on Panel A, for long stocks, we note that the negative predictive power of AMFs' trading disappears, given that the coefficient on Δ%Fund(q-6, q-1) becomes sub-

[7] We add SIZE and BM to the set, as they have been shown to be related to future stock returns.

stantially lower in magnitude and statistically insignificant. Moreover, the coefficient on SIZE is -0.13 with a t-statistic of -3.46, indicating that the negative predictive ability of AMFs' buying and selling activity is largely driven by their strong trading preference for large cap stocks. This is also supported by the evidence shown in Table 5 that AMFs tend to buy (sell) stocks with large (small) market cap. On the other hand, Panel B shows that the predictive power of AMFs' short-selling and covering activity still exists (though weakened) after controlling for SIZE and BM: the coefficient on Δ%Fund(q-6,q-1) is -0.27 (t-statistic=-2.06). We also note that the coefficient on SIZE is -0.12 with a t-statistic of -2.30. The results suggest that AMFs' shorting and covering contain predictive information for future returns beyond that derived from size and book-to-market characteristics.

Finally, in Columns (9)–(12), we further add the nine anomaly characteristics studied in this paper as control variables. As a result, for long stocks (Panel A), the coefficient on Δ%Fund(q-6,q-1) is virtually unchanged, confirming that the negative predictive power of AMFs' buying and selling for future returns depends exclusively on their adverse exposure towards the size characteristic. For shorted stocks (Panel B), however, the coefficient on Δ%Fund(q-6,q-1) becomes statistically insignificant, suggesting that the predictive ability of Δ%Fund is related to the firm size and the nine anomaly characteristics.

In general, the results based on AMFs' long stock positions suggest that AMFs' buying and selling have negative predictive power for future stock returns, but this predictability is largely explained by their preference for large cap stocks. On the contrary, the results based on AMFs' short stock positions suggest that AMFs' short-selling and covering activity can predict future stock returns. However, these activity does not contain additional information beyond what is contained in size and the nine anomaly characteristics.

4 Robustness

In the baseline analysis, we show that AMFs in aggregate trade on the "right" side of stock market anomalies, based on either of their long and short equity positions. We also find that while AMFs' buying and selling activity does not seem to generate alpha, their short-selling and covering activity produces superior future abnormal returns. In this section, we perform several robustness tests. First, we examine whether the results are robust across different fund categories. Second, we investigate the robustness of the results over time.

4.1 Sub-sample analysis

Recall that our sample consists of five fund categories as classified by Morningstar: Long-short Equity, Market Neutral, Multialternative, 130–30, and Bear Market. A natural question is then whether our main results hold for different fund categories. To this end, we repeat our baseline analysis for individual categories and report the average results across the nine anomalies in Table 7.

Panel A of Table 7 investigates the anomaly trading behavior of AMFs by fund category. From the first sub-panel (Panel A1), we can see that based on their long equity positions, the funds in all categories (except for bear market funds) on average trade in the "right" direction implied by anomalies, although to different extents.[8] For instance, the differences in Δ%Fund between the underpriced and overpriced groups are 2.57%, 1.87%, 0.79%, and 2.06% with t-statistics of 5.08, 2.83, 2.39, and 3.17, respectively, for Long-short Equity, Market Neutral, Multialternative, and 130–30. The second sub-panel (Panel A2) shows very similar patterns except for bear market

[8]The results in Panel A1 for bear market funds are missing due to the lack of data on their long stock positions.

funds, based on the funds' short equity positions. For example, for the remaining four fund categories, the differences in Δ%Fund between the underpriced and overpriced groups range from -0.80 to -3.61, with t-statistics ranging from -2.12 to -8.30.

In Panel B of Table 7, we examine AMFs' anomaly trading performance for each of the five categories. In general, the first sub-panel (Panel B1) shows that based on AMFs' long stock positions, the stocks the funds buy do not significantly outperform those they sell. The only exception is that the difference in annualized alpha between the underpriced stocks bought and sold by market neutral funds is 4.51% (t-statistics=2.03). The results based on AMFs' short equity positions in the second sub-panel (Panel B2) show that anomaly stocks sold short by the funds underperform those they cover for four (three) out of the five fund categories in the overpriced (underpriced) group.[9] In summary, the results based on individual fund categories largely confirm our baseline findings.

4.2 Sub-period analysis

To investigate whether our main results are robust over time, we split our full sample into two sub-periods of 2002:7–2009:6 and 2009:7–2016:12 and repeat the main analysis. Table 8 presents the results averaged across the nine anomalies on AMFs' anomaly trading behavior and the performance of anomaly portfolios conditional on their trading, respectively, in Panels A and B, for both sub-periods. Panel A shows that AMFs exhibit significant preferences for anomaly-implied mispriced stocks in their trading in both periods. This is consistent with our baseline finding that AMFs tend to buy underpriced stocks and short-sell overpriced ones. Moreover, their anomaly

[9]It is worth pointing out that even though the stocks sold short by bear market funds underperform those they cover in both overpriced and underpriced groups, we do not detect any anomaly trading activity in their trading. Therefore, the underperformance cannot be attributed to anomaly related trading.

trading appears to be stronger during the first sub-period, as evidenced by the magnitudes of the differences in average Δ%Fund between the underpriced and overpriced groups (11.79% vs. 5.14% based on AMFs' long stock positions; -13.60% vs. -7.36% based on their short stock positions). From Panel B, we can see that AMFs' buying and selling combined do not produce positive abnormal returns in both periods. In contrast, their short-selling and covering activity appears to generate alpha in both periods, as the stocks they short-sell underperform those they cover in both the underpriced and overpriced groups. Overall, our sub-period analysis confirms the baseline results of this paper, suggesting that our results are robust over time.

5 Concluding remarks

The existing literature presents mixed evidence on whether institutional investors can trade on well-known stock market anomalies, mostly based on their long-side portfolio holdings [e.g., Lewellen (2011); Akbas et al. (2015); Edelen et al. (2016); Calluzzo et al. (2017)]. However, the asset pricing literature suggests that overpricing should be more prevalent than underpricing due to limits to arbitrage [e.g., Miller (1977)] and that market anomalies derive their profitability mainly from selling short overpriced stocks [e.g., Stambaugh et al. (2012, 2015); Avramov et al. (2013)]. As a result, using only long-side portfolio holdings may understate the ability of institutional investors, especially those who can freely adopt alternative strategies such as short selling, to exploit market anomalies.

In this paper, we provide new empirical evidence by investigating the anomaly trading behavior of a sample of mutual funds mimicking hedge fund strategies, namely alternative mutual funds (AMFs), based on both of their long and short equity positions. Consistent with the sophisticated investor hypothesis, the results show that AMFs trade according to anomaly prescriptions by buying underpriced stocks and selling short overpriced ones. Based on their long positions, we do not find compelling evidence that AMFs buys and sells are related to superior abnormal returns. However, based on their short positions, AMFs in aggregate earn significantly positive abnormal returns in anomaly stocks that they short-sell and cover. Finally, we show that AMF's short-selling and covering activity does not contain additional private information in predicting future stock returns, beyond what is contained in size and the nine anomaly characteristics. Overall, the results indicate that AMFs are sophisticated investors and their short positions are more informative relative to their long positions.

Our findings have several important implications regarding the role that institutional investors and limits-of-arbitrage might play in well-known stock market anomalies. In particular, McLean and Pontiff (2016) document that anomaly returns decline by more than 50% in the post-publication period, which largely coincides with our sample period of 2002–2016. Our results suggest that AMFs are "smart" institutional investors who may play the role of short arbitragers in correcting cross-sectional mispricing.

Moreover, Agarwal et al. (2009) show that about half of AMFs have managers with hedge fund experience. Therefore, it is not unreasonable to argue that their trading behavior would provide valuable insight into hedge funds' trading strategies, to the extent that managers manage AMFs and hedge funds in a similar way. Although the short positions of hedge funds are typically undisclosed, one might infer the potential role of hedge funds as short arbitragers in correcting stock return anomalies based on the disclosed short positions of AMFs.

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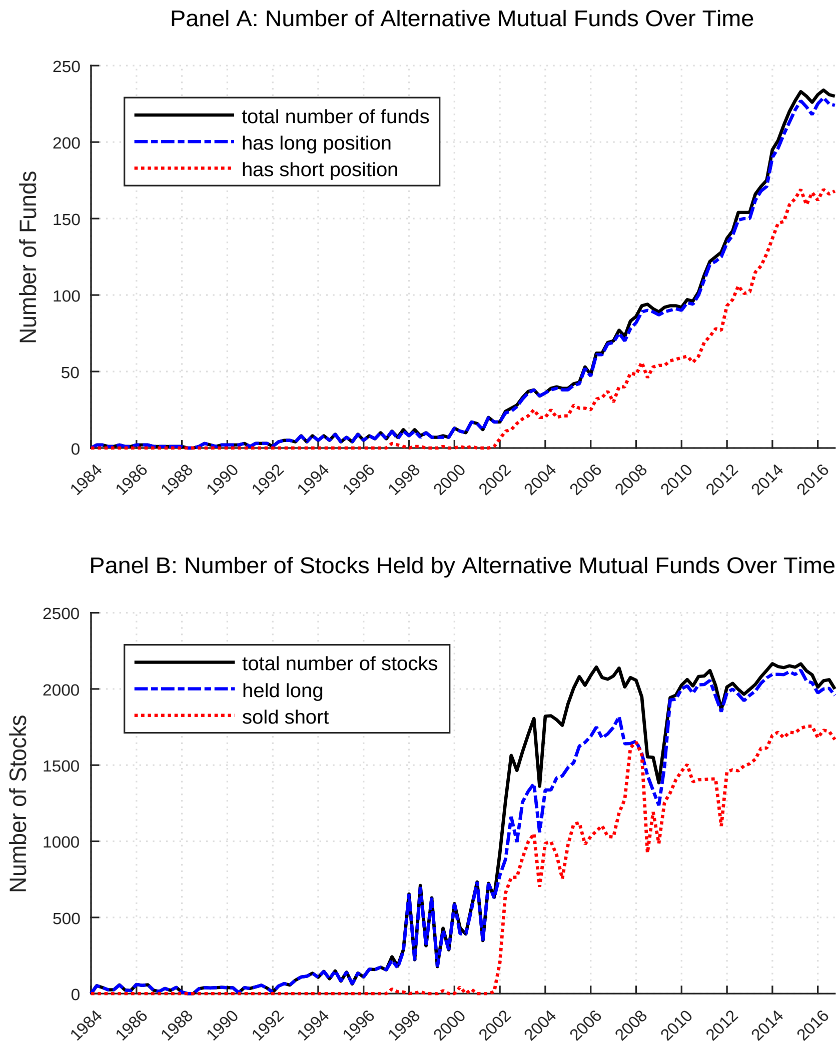

Figure 1. The number of alternative mutual funds and stocks held over time

This figure plots the number of alternative mutual funds (AMFs) and the number of stocks held over time. In Panel A, the black solid line shows the number of AMFs, and the blue dashed and red dotted lines show the number of AMFs with long and short positions, respectively. In Panel B, the black solid line depicts the number of stocks held, and the blue dashed and red dotted lines depict the number of stocks held long and sold short by AMFs, respectively.

Table 1. Properties of stock market anomalies

This table presents properties of returns for the nine stock market anomalies during the sample period of 1984–2016. Panels A and B report the annualized three-factor alphas (in percentage) of the long, short, and long-short value-weighted anomaly portfolios based on all stocks with non-missing anomaly characteristics in the CRSP universe and those held only by alternative mutual funds (AMFs), respectively. The long (short) leg is the best- (worst-) performing decile portfolio implied by the indicated anomaly, and the long-short portfolio is the difference between the best- and worst-performing deciles. The last column (AVG) refers to a combination strategy that takes equal positions across the nine anomalies. Figures in brackets are heteroskedasticity-adjusted t-statistics. Panel C presents the correlation matrix among the long-short benchmark-adjusted returns of the nine anomalies. Following Stambaugh et al. (2012), we define the benchmark-adjusted returns as the sum of the intercept and the residuals from the regression of a long-short strategy's monthly excess returns on the Fama and French (1993) three factors. Figures in parentheses are p-values.

	Accurals (ACC)	Asset Growth (AG)	Gross Profitability (GP)	Investment to Assets (ITA)	Momentum (MOM)	Net Operating Assets (NOA)	Net Stock Issuance (NSI)	O-Score (OSC)	Return on Assets (ROA)	Average (AVG)
Panel A: CRSP										
Long	3.70	0.60	4.16	1.32	-0.12	3.89	2.56	1.97	3.47	2.40
	[1.82]	[0.39]	[3.18]	[1.02]	[-0.05]	[2.01]	[2.22]	[1.87]	[3.32]	[3.27]
Short	-3.45	-4.47	-3.71	-4.01	-8.20	-6.14	-4.77	-4.25	-2.28	-4.59
	[-1.99]	[-2.68]	[-1.61]	[-2.22]	[-3.27]	[-3.43]	[-2.99]	[-2.28]	[-0.90]	[-3.76]
Long-Short	7.16	5.07	7.87	5.33	8.09	10.04	7.33	6.22	5.75	6.98
	[2.72]	[2.39]	[2.69]	[2.49]	[2.05]	[3.53]	[3.94]	[2.93]	[2.08]	[5.04]
Panel B: AMFs										
Long	1.28	-0.49	4.23	1.26	0.67	4.76	1.66	1.80	4.30	2.16
	[0.92]	[-0.73]	[2.90]	[0.94]	[0.59]	[2.60]	[1.42]	[1.88]	[3.63]	[2.97]
Short	-1.72	-3.79	-3.51	-3.32	-5.78	-6.29	-3.50	-0.36	-1.11	-3.28
	[-1.55]	[-2.49]	[-1.50]	[-1.79]	[-1.94]	[-3.47]	[-2.32]	[-0.21]	[-0.49]	[-2.98]
Long-Short	2.99	3.29	7.74	4.58	6.46	11.05	5.17	2.17	5.41	5.44
	[1.89]	[2.16]	[2.86]	[2.07]	[1.99]	[3.93]	[2.79]	[1.46]	[1.77]	[4.30]
Panel C: Correlations										
	ACC	AG	GP	ITA	MOM	NOA	NSI	OSC	ROA	
ACC	1.00									
	(1.000)									
AG	0.18									
	(0.000)									
GP	-0.15	0.23								
	(0.003)	(0.000)								
ITA	0.17	0.29	0.09							
	(0.001)	(0.000)	(0.085)							
MOM	0.11	0.12	0.09	0.08						
	(0.036)	(0.016)	(0.066)	(0.095)						
NOA	0.36	0.32	0.08	0.35	0.25					
	(0.000)	(0.000)	(0.120)	(0.000)	(0.000)					
NSI	-0.01	0.24	0.21	0.31	0.00	0.27				
	(0.788)	(0.000)	(0.000)	(0.000)	(0.980)	(0.000)				
OSC	0.02	0.03	0.20	0.04	0.07	0.13	0.14			
	(0.657)	(0.555)	(0.000)	(0.459)	(0.176)	(0.012)	(0.004)			
ROA	-0.17	0.12	0.41	0.03	0.23	0.06	0.16	0.40	1.00	
	(0.001)	(0.013)	(0.000)	(0.603)	(0.000)	(0.237)	(0.002)	(0.000)	(1.000)	

Table 2. Characteristics of alternative mutual funds and stocks held

This table presents summary statistics of alternative mutual funds (AMFs) and the stocks they hold during the sample period of 2002–2016. Panel A presents the mean, standard deviation, and the quantile distribution of fund characteristics, including fund total net assets (TNA), age (AGE), turnover ratio (TURN), and annual expense ratio (EXPENSE). Panel B presents the time-series averages of characteristic rank scores of (1) the CRSP portfolio which consists of all stocks with non-missing characteristics in the CRSP universe, (2) the long portfolio which includes all stocks long by AMFs, and (3) the short portfolio which contains all stock shorted by AMFs, as well as the differences among the three portfolios. The characteristic rank score is the stock's decile rank on the characteristic relative to all stocks in the CRSP portfolio, with decile 10 (1) being the best- (worst-) performing stocks. The portfolio-level characteristic rank score is thus the market-capitalization weighted average rank score of all stocks held in the portfolio. The last row (AVG) refers to the mean values across the 11 stock characteristics, including book-to-market (BM), size (SIZE), and the nine anomalies studied in this paper. Figures in brackets are heteroskedasticity-adjusted t-statistics.

Panel A: Fund characteristics

			Quantile Distribution				
	Mean	StdDev	P10	P25	P50	P75	P90
TNA ($mil)	245.38	623.17	5.14	12.21	41.00	158.88	685.51
AGE (years)	6.70	6.04	1.33	2.58	5.00	9.00	14.25
TURN (%)	297.83	650.55	49.50	100.07	182.47	319.80	517.60
EXPENSE (%)	1.95	0.55	1.36	1.60	1.90	2.24	2.65

Panel B: Stock characteristics

	CRSP	AMFs		Difference					
		Long	Shorted						
	(1)	(2)	(3)	(2) - (1)		(3) - (1)		(2) - (3)	
ACC	5.67	5.79	5.68	0.12	[3.26]	0.01	[0.34]	0.11	[2.27]
AG	5.22	5.11	5.14	-0.10	[-2.12]	-0.08	[-2.04]	-0.02	[-0.35]
BM	3.95	3.74	3.57	-0.21	[-4.16]	-0.38	[-7.61]	0.17	[2.06]
GP	5.76	5.97	5.78	0.22	[6.48]	0.02	[0.34]	0.20	[2.42]
ITA	5.43	5.48	5.33	0.05	[1.44]	-0.10	[-2.91]	0.15	[2.89]
MOM	5.68	5.78	5.19	0.10	[1.73]	-0.49	[-7.55]	0.59	[6.83]
NOA	5.73	6.01	5.74	0.27	[13.21]	0.01	[0.18]	0.27	[5.10]
NSI	6.93	7.26	6.97	0.33	[8.57]	0.04	[0.91]	0.29	[4.22]
OSC	7.81	8.60	7.84	0.80	[50.23]	0.03	[0.79]	0.77	[14.72]
ROA	7.18	7.71	7.00	0.53	[35.28]	-0.18	[-5.02]	0.71	[18.17]
SIZE	1.56	1.14	1.32	-0.42	[-54.83]	-0.24	[-18.38]	-0.17	[-10.64]
AVG	5.54	5.69	5.41	0.15	[9.80]	-0.12	[-9.49]	0.28	[11.22]

Table 3. Alternative mutual funds' trading on market anomalies

This table presents trading activity of alternative mutual funds (AMFs) on the nine stock market anomalies over the sample period of 2002–2016. We measure trading using two measures: (1) Δ%Fund, defined as the annualized change (in percentage) in the number of AMFs scaled by the average number of AMFs holding stocks in the same market capitalization decile at the beginning of the trading window; and (2) Δ%Shr, defined as the annualized change (in percentage) in fraction of shares held by AMFs. Both measures are calculated over a trading window of six quarters prior to the anomaly portfolio formation date. "Underpriced" ("Overpriced") refers to the top (bottom) 30% stocks ranked by the indicated anomaly variable, and "Neutral" corresponds to the middle 40%. Panels A and B show the results based on AMF's long and short equity positions, respectively. In both panels, we compute the mean values across the nine anomalies in the last section ("AVG"). Figures in brackets are heteroskedasticity-adjusted t-statistics.

Panel A: Long stocks

	ACC				AG				GP				ITA				MOM			
	%Fund		%Shr		%Fund		%Shr		%Fund		%Shr		%Fund		%Shr		%Fund		%Shr	
Underpriced	39.26		0.21		32.85		0.28		34.40		0.10		37.91		0.29		40.90		0.14	
Neutral	35.30		0.10		33.80		0.11		35.15		0.18		33.95		0.12		24.98		0.12	
Overpriced	26.58		0.17		35.22		0.09		32.73		0.14		30.52		0.08		13.74		0.08	
U-N	3.96	[2.36]	0.11	[1.04]	-0.95	[-0.56]	0.17	[1.31]	-0.75	[-0.63]	-0.09	[-1.21]	3.96	[3.80]	0.17	[1.22]	15.92	[17.96]	0.02	[0.48]
O-N	-8.72	[-3.33]	0.07	[1.18]	1.42	[0.61]	-0.03	[-1.32]	-2.42	[-1.61]	-0.04	[-0.48]	-3.43	[-2.58]	-0.05	[-2.07]	-11.24	[-12.86]	-0.04	[-1.48]
U-O	12.68	[6.52]	0.04	[0.36]	-2.37	[-0.71]	0.20	[1.52]	1.67	[1.01]	-0.04	[-0.73]	7.39	[4.03]	0.21	[1.58]	27.15	[18.92]	0.06	[1.82]

	NOA				NSI				OSC				ROA				AVG			
	%Fund		%Shr		%Fund		%Shr		%Fund		%Shr		%Fund		%Shr		%Fund		%Shr	
Underpriced	36.83		0.26		33.44		0.21		30.01		0.08		31.16		0.06		38.02		0.20	
Neutral	34.52		0.09		33.38		0.12		24.92		0.08		25.73		0.08		33.83		0.11	
Overpriced	31.46		0.15		36.17		0.09		21.44		0.24		18.44		0.26		29.78		0.16	
U-N	2.31	[1.52]	0.16	[1.29]	0.06	[0.03]	0.09	[1.13]	5.10	[7.06]	0.00	[-0.22]	5.43	[5.74]	-0.01	[-2.19]	4.19	[4.33]	0.09	[1.33]
O-N	-3.06	[-2.24]	0.06	[1.08]	2.79	[1.27]	-0.03	[-1.40]	-3.48	[-2.79]	0.16	[2.03]	-7.29	[-8.88]	0.18	[2.18]	-4.06	[-4.36]	0.05	[1.15]
U-O	5.37	[3.60]	0.11	[0.75]	-2.73	[-1.50]	0.12	[1.49]	8.58	[5.15]	-0.17	[-2.05]	12.72	[8.23]	-0.19	[-2.36]	8.24	[5.60]	0.04	[0.96]

Panel B: Shorted stocks

	ACC				AG				GP				ITA				MOM			
	%Fund		%Shr		%Fund		%Shr		%Fund		%Shr		%Fund		%Shr		%Fund		%Shr	
Underpriced	14.63		0.05		11.92		0.05		14.79		0.05		11.58		0.04		7.42		0.03	
Neutral	14.23		0.04		13.84		0.04		14.85		0.05		14.01		0.04		11.03		0.04	
Overpriced	22.17		0.08		24.10		0.07		19.85		0.06		23.46		0.07		17.09		0.07	
U-N	0.41	[0.31]	0.01	[2.21]	-1.92	[-2.03]	0.01	[1.09]	-0.06	[-0.07]	0.01	[0.82]	-2.43	[-2.29]	0.00	[-0.45]	-3.61	[-4.41]	-0.01	[-2.73]
O-N	7.94	[5.64]	0.03	[4.05]	10.26	[6.70]	0.03	[2.48]	5.00	[4.51]	0.01	[1.99]	9.44	[6.38]	0.03	[3.80]	6.06	[8.32]	0.04	[9.01]
U-O	-7.53	[-3.93]	-0.03	[-3.42]	-12.18	[-6.78]	-0.02	[-1.28]	-5.05	[-3.49]	-0.01	[-0.94]	-11.87	[-8.48]	-0.03	[-2.99]	-9.67	[-8.13]	-0.05	[-7.33]

	NOA				NSI				OSC				ROA				AVG			
	%Fund		%Shr		%Fund		%Shr		%Fund		%Shr		%Fund		%Shr		%Fund		%Shr	
Underpriced	16.79		0.06		11.84		0.04		9.58		0.03		9.80		0.03		12.95		0.04	
Neutral	13.22		0.04		15.18		0.05		11.91		0.04		10.78		0.04		14.36		0.05	
Overpriced	20.38		0.06		24.49		0.07		16.22		0.07		17.65		0.08		22.70		0.07	
U-N	3.57	[3.31]	0.01	[1.86]	-3.35	[-2.97]	-0.01	[-3.23]	-2.32	[-4.86]	-0.01	[-5.33]	-0.98	[-1.72]	0.00	[-1.84]	-1.41	[-3.17]	0.00	[-0.52]
O-N	7.16	[5.48]	0.02	[2.04]	9.31	[4.64]	0.01	[1.45]	4.32	[6.81]	0.02	[5.66]	6.87	[8.86]	0.04	[7.90]	8.34	[8.15]	0.03	[4.65]
U-O	-3.60	[-2.63]	-0.01	[-0.82]	-12.65	[-5.58]	-0.03	[-3.27]	-6.64	[-8.50]	-0.04	[-7.93]	-7.85	[-8.23]	-0.04	[-8.29]	-9.76	[-7.98]	-0.03	[-4.35]

Table 4. Alternative mutual funds' trading and abnormal anomaly returns

This table presents annualized three-factor alphas (in percentage) of anomaly portfolios conditional on alternative mutual funds (AMFs)' trading during the sample period of 2002–2016. We measure trading by Δ%Fund, defined as the change in fraction of AMFs over the six-quarter trading window prior to anomaly portfolio formation date. Panels A and B report the results based on AMFs' long and short equity positions, respectively. In each panel, we construct four value-weighted conditional anomaly portfolios for each of the nine anomalies by taking the intersection of the top and bottom 30% of the indicated anomaly variable with the top and bottom 20% of Δ%Fund. We also construct four portfolios that take equal positions across the nine anomalies in the last section ("AVG"). "Underpriced" ("Overpriced") refers to the top (bottom) 30% stocks ranked by the anomaly variable. "Buy" ("Sell") and "Short-sell" ("Cover") refer to the top (bottom) 20% stocks ranked by Δ%Fund for those held long and sold short by AMFs, respectively. The alpha is estimated by regressing portfolio monthly excess returns from July of year t to June of year t+1 on the Fama and French (1993) three factors. Figures in brackets are heteroskedasticity-adjusted t-statistics.

Panel A: Long stocks

	ACC			AG			GP			ITA			MOM		
	Buy	Sell	Difference	Buy	Sell	Difference	Buy	Sell	Difference	Buy	Sell	Difference	Buy	Sell	Difference
Underpriced	0.32	1.28	-0.96	2.51	2.77	-0.26	3.70	0.80	2.90	4.34	3.11	1.23	1.26	1.83	-0.57
	[0.11]	[0.39]	[-0.25]	[1.25]	[1.18]	[-0.08]	[1.24]	[0.32]	[0.74]	[1.84]	[1.08]	[0.33]	[0.47]	[0.64]	[-0.15]
Overpriced	-4.71	1.48	-6.19	4.22	-0.50	4.72	-2.95	1.33	-4.28	7.66	0.06	7.61	4.01	2.69	1.32
	[-1.32]	[0.50]	[-1.35]	[1.26]	[-0.18]	[1.16]	[-0.98]	[0.46]	[-1.18]	[2.43]	[0.02]	[1.51]	[0.94]	[0.85]	[0.28]

	NOA			NSI			OSC			ROA			AVG		
	Buy	Sell	Difference	Buy	Sell	Difference	Buy	Sell	Difference	Buy	Sell	Difference	Buy	Sell	Difference
Underpriced	5.76	-1.02	6.79	2.05	2.28	-0.23	6.40	3.00	3.40	6.33	4.59	1.74	3.15	2.37	0.78
	[2.07]	[-0.46]	[1.98]	[0.90]	[1.05]	[-0.06]	[2.49]	[1.32]	[0.92]	[2.41]	[2.05]	[0.48]	[1.96]	[1.55]	[0.32]
Overpriced	-5.32	-0.76	-4.56	3.13	0.33	2.80	-2.41	-2.56	0.15	-9.87	-8.10	-1.77	-1.31	-0.32	-0.99
	[-1.92]	[-0.22]	[-1.09]	[0.84]	[0.11]	[0.56]	[-0.81]	[-0.92]	[0.04]	[-2.67]	[-2.39]	[-0.40]	[-0.67]	[-0.15]	[-0.40]

Panel B: Shorted stocks

	ACC			AG			GP			ITA			MOM		
	Short-sell	Cover	Difference	Short-sell	Cover	Difference	Short-sell	Cover	Difference	Short-sell	Cover	Difference	Short-sell	Cover	Difference
Underpriced	-2.46	2.13	-4.58	1.38	1.57	-0.19	-1.38	1.12	-2.50	-6.47	2.60	-9.07	-2.20	2.29	-4.49
	[-0.72]	[0.76]	[-1.27]	[0.38]	[0.62]	[-0.04]	[-0.47]	[0.46]	[-0.67]	[-1.75]	[1.39]	[-2.29]	[-0.65]	[1.02]	[-1.30]
Overpriced	-4.74	0.22	-4.96	-2.82	3.33	-6.15	-1.82	-3.02	1.20	-4.79	-0.15	-4.64	-0.83	6.41	-7.24
	[-2.04]	[0.07]	[-1.30]	[-1.40]	[1.19]	[-2.00]	[-0.63]	[-1.07]	[0.33]	[-1.73]	[-0.05]	[-1.34]	[-0.27]	[2.41]	[-2.02]

	NOA			NSI			OSC			ROA			AVG		
	Short-sell	Cover	Difference	Short-sell	Cover	Difference	Short-sell	Cover	Difference	Short-sell	Cover	Difference	Short-sell	Cover	Difference
Underpriced	0.15	1.27	-1.12	-3.36	1.18	-4.54	-2.72	2.72	-5.44	-2.87	5.23	-8.10	-2.09	2.28	-4.37
	[0.05]	[0.58]	[-0.30]	[-1.15]	[0.70]	[-1.30]	[-1.09]	[1.50]	[-1.79]	[-1.10]	[2.65]	[-2.59]	[-1.21]	[1.85]	[-2.09]
Overpriced	-5.16	-4.37	-0.79	-5.28	4.38	-9.66	-3.99	3.51	-7.50	-5.33	-3.95	-1.38	-3.80	1.17	-4.96
	[-2.11]	[-1.31]	[-0.26]	[-2.19]	[1.23]	[-2.19]	[-1.53]	[1.30]	[-2.01]	[-1.70]	[-1.24]	[-0.35]	[-2.19]	[0.67]	[-2.53]

Table 5. Characteristics of anomaly portfolios conditional on alternative mutual funds' trading

This table presents average characteristics across the nine anomalies of stocks held in anomaly portfolios conditional on alternative mutual funds (AMFs)' trading over the sample period of 2002–2016. We measure trading by Δ%Fund, defined as the change in fraction of AMFs over the six-quarter trading window prior to anomaly portfolio formation date. Panels A and B report the results based on AMFs' long and short equity positions, respectively. In each panel, we construct four value-weighted conditional anomaly portfolios for each of the nine anomalies by taking the intersection of the top and bottom 30% of the anomaly variable with the top and bottom 20% of Δ%Fund. "Underpriced" ("Overpriced") refers to the top (bottom) 30% stocks ranked by the anomaly variable. "Buy" ("Sell") and "Short-sell" ("Cover") refer to the top (bottom) 20% stocks ranked by Δ%Fund for those held long and sold short by AMFs, respectively. %NSTOCKS is the count of stocks in each portfolio divided by the total number of stocks in the four portfolios. MKTCAP is the average market capitalization in millions 2016 dollars. BM is the average book-to-market ratio. TURN is the average monthly turnover ratio over the previous year. IVOL is the average annualized volatility of monthly residuals from the Fama and French (1993) three-factor model estimated over the past 36 months. Figures in brackets are heteroskedasticity-adjusted t-statistics.

	%NSTOCKS (%)			MKTCAP (in 2016 $Mil)			BM			TURN (%)			IVOL (%)		
Panel A: Long stocks															
	Buy	Sell	B-S	Buy	Sell	B-S	Buy	Sell	B-S	Buy	Sell	B-S	Buy	Sell	B-S
Underpriced	35.16	18.58	16.57	13,299.93	6,052.85	7,247.08	0.50	0.52	-0.02	24.31	24.42	-0.11	33.68	33.87	-0.19
			[8.84]			[3.40]			[-0.88]			[-0.13]			[-0.18]
Overpriced	25.57	20.69	4.87	7,759.68	4,165.85	3,593.83	0.58	0.62	-0.04	25.53	27.17	-1.63	36.50	37.00	-0.50
			[2.69]			[2.60]			[-1.68]			[-1.75]			[-0.47]
Panel B: Shorted stocks															
	Short-sell	Cover	S-C	Short-sell	Cover	S-C	Short-sell	Cover	S-C	Short-sell	Cover	S-C	Short-sell	Cover	S-C
Underpriced	24.69	22.45	2.24	7,439.62	10,349.57	-2,909.94	0.41	0.46	-0.04	28.43	24.32	4.11	37.02	27.36	8.45
			[1.50]			[-1.60]			[-4.39]			[4.61]			[6.90]
Overpriced	34.56	18.30	16.26	3,990.49	6,203.67	-2,213.19	0.47	0.56	-0.09	30.24	26.66	3.58	40.38	31.05	7.59
			[8.55]			[-3.28]			[-4.97]			[6.16]			[5.40]

Table 6. Alternative mutual funds' trading and future stock returns

This table reports Fama-McBeth regression results of monthly stock excess returns on alternative mutual funds (AMFs)' trading and a variety of stock characteristics over the sample period of 2002:7–2016:12. We measure trading by Δ%Fund, defined as the change in fraction of AMFs over the six-, four-, two-, or one-quarter trading window prior to the anomaly portfolio formation date. In Columns (1)–(4), we regress excess returns on Δ%Fund only. Columns (5)–(8) control for firm size (SIZE) and book-to-market ratio (BM), and Columns (9)–(12) further control for the nine anomaly characteristics. Panels A and B present the results based on stocks held long and sold short by AMFs, respectively. Figures in brackets are Newey-West adjusted t-statistics.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Long stocks												
Δ%Fund(q-6, q-1)	-0.33				-0.05				-0.06			
	[-2.38]				[-1.59]				[-0.88]			
Δ%Fund(q-4, q-1)		-0.19				-0.09				-0.06		
		[-2.08]				[-1.12]				[-1.06]		
Δ%Fund(q-2, q-1)			-0.10				-0.06				-0.04	
			[-1.76]				[-1.31]				[-1.20]	
Δ%Fund(q-1)				-0.02				-0.03				-0.01
				[-0.81]				[-1.06]				[-0.26]
SIZE					-0.13	-0.14	-0.14	-0.14	-0.17	-0.17	-0.18	-0.18
					[-3.46]	[-3.42]	[-3.46]	[-3.49]	[-5.49]	[-5.57]	[-5.38]	[-5.07]
BM					0.05	0.06	0.04	0.06	0.05	0.04	0.03	0.09
					[0.29]	[0.31]	[0.20]	[0.35]	[0.27]	[0.20]	[0.19]	[0.48]
ACC									0.29	0.28	0.17	0.14
									[0.38]	[0.36]	[0.23]	[0.18]
AG									0.10	0.10	0.07	0.06
									[0.53]	[0.51]	[0.35]	[0.32]
GP									-0.63	-0.61	-0.61	-0.59
									[-2.25]	[-2.20]	[-2.15]	[-2.05]
ITA									0.09	0.11	0.16	0.12
									[0.18]	[0.21]	[0.31]	[0.23]
MOM									-0.80	-0.80	-0.80	-0.79
									[-2.04]	[-2.03]	[-2.01]	[-2.00]
NOA									0.39	0.37	0.36	0.41
									[2.17]	[2.01]	[1.93]	[2.11]
NSI									-0.32	-0.28	-0.18	-0.23
									[-0.63]	[-0.55]	[-0.34]	[-0.42]
OSC									0.10	0.10	0.10	0.09
									[1.99]	[1.97]	[1.96]	[1.76]
ROA									14.18	14.01	14.18	14.58
									[7.29]	[7.17]	[7.03]	[7.28]
Panel B: Shorted stocks												
Δ%Fund(q-6, q-1)	-0.37				-0.27				-0.12			
	[-2.45]				[-2.06]				[-0.83]			
Δ%Fund(q-4, q-1)		-0.21				-0.15				-0.07		
		[-1.93]				[-1.51]				[-0.26]		
Δ%Fund(q-2, q-1)			-0.06				-0.02				-0.01	
			[-1.00]				[-0.34]				[-0.12]	
Δ%Fund(q-1)				-0.08				-0.05				-0.07
				[-2.30]				[-1.30]				[-1.69]
SIZE					-0.12	-0.12	-0.13	-0.13	-0.16	-0.16	-0.16	-0.16
					[-2.24]	[-2.25]	[-2.29]	[-2.30]	[-3.81]	[-3.82]	[-3.81]	[-3.86]
BM					0.04	0.04	0.04	0.03	-0.04	-0.06	-0.03	-0.05
					[0.17]	[0.15]	[0.15]	[0.10]	[-0.17]	[-0.26]	[-0.13]	[-0.22]
ACC									0.31	0.36	0.31	0.17
									[0.39]	[0.45]	[0.40]	[0.22]
AG									0.09	0.11	0.10	0.07
									[0.49]	[0.63]	[0.59]	[0.39]
GP									-0.61	-0.62	-0.62	-0.60
									[-1.97]	[-2.00]	[-2.02]	[-1.89]
ITA									0.10	0.14	0.11	0.15
									[0.20]	[0.26]	[0.21]	[0.30]
MOM									-0.81	-0.79	-0.78	-0.77
									[-1.99]	[-1.94]	[-1.88]	[-1.87]
NOA									0.31	0.30	0.33	0.30
									[1.99]	[1.82]	[2.03]	[1.81]
NSI									0.02	-0.02	0.08	0.23
									[0.04]	[-0.03]	[0.15]	[0.44]
OSC									0.11	0.12	0.12	0.12
									[2.26]	[2.43]	[2.54]	[2.45]
ROA									9.31	8.97	8.72	8.16
									[4.12]	[4.03]	[4.17]	[3.97]

Table 7. Anomaly trading and performance of conditional anomaly portfolios by fund category

This table presents anomaly trading activity of alternative mutual funds (AMFs) and abnomal returns of anomaly portfolios conditional on AMFs' trading by fund category in Panels A and B, respectively, during the sample period of 2002–2016. Our sample consists of five fund categories as classified by Morningstar: Long-short Equity, Market Neutral, Multialternative, 130–30, and Bear Market. For each fund category, we report the results averaged across the nine anomalies. In Panel A, We measure trading by Δ%Fund, defined as the change in fraction of AMFs over the six-quarter trading window prior to the anomaly portfolio formation date. In Panel B, we construct four value-weighted conditional anomaly portfolios by taking the intersection of the top and bottom 30% of the anomaly variable with the top and bottom 20% of Δ%Fund, and calculate annualized three-factor alphas (in percentage) of these portfolios. "Underpriced" ("Overpriced") refers to the top (bottom) 30% stocks ranked by the anomaly variable, and "Neutral" corresponds to the middle 40%. "Buy" ("Sell") and "Short-sell" ("Cover") refer to the top (bottom) 20% stocks ranked by Δ%Fund for those held long and sold short by AMFs, respectively. Figures in brackets are heteroskedasticity-adjusted t-statistics.

	Long-short Equity			Market Neutral			Multialternative			130-30			Bear Market		
Panel A: Anomaly trading															
A1. Long stocks															
	Δ%Fund			Δ%Fund			Δ%Fund			Δ%Fund					
Underpriced	11.27			12.65			7.16			6.57					
Neutral	10.71			10.85			6.64			5.38					
Overpriced	8.70			10.78			6.38			4.50					
U-N	0.56	[1.28]		1.80	[3.21]		0.52	[3.37]		1.19	[1.62]				
O-N	-2.01	[-3.40]		-0.07	[-0.08]		-0.27	[-0.95]		-0.88	[-1.98]				
U-O	2.57	[5.08]		1.87	[2.83]		0.79	[2.39]		2.06	[3.17]				
A2. Shorted stocks															
	Δ%Fund			Δ%Fund			Δ%Fund			Δ%Fund			Δ%Fund		
Underpriced	4.70			4.18			2.45			0.37			0.62		
Neutral	4.45			4.68			2.58			0.48			0.69		
Overpriced	7.06			7.79			3.24			1.52			0.41		
U-N	0.25	[1.11]		-0.50	[-1.98]		-0.14	[-1.33]		-0.11	[-0.74]		-0.07	[-0.19]	
O-N	2.61	[6.39]		3.11	[5.78]		0.66	[2.55]		1.04	[2.36]		-0.29	[-1.15]	
U-O	-2.35	[-5.56]		-3.61	[-8.30]		-0.80	[-2.53]		-1.15	[-2.12]		0.22	[0.78]	
Panel B: Abnormal returns															
B1. Long stocks															
	Buy	Sell	Difference	Buy	Sell	Difference	Buy	Sell	Difference	Buy	Sell	Difference			
Underpriced	1.41	1.88	-0.47	2.70	-1.81	4.51	0.17	3.30	-3.14	1.77	-0.18	1.95			
	[0.78]	[0.82]	[-0.19]	[1.40]	[-1.00]	[2.03]	[0.09]	[1.20]	[-0.94]	[1.60]	[-0.11]	[0.91]			
Overpriced	-2.47	-5.86	3.39	-1.29	1.79	-3.08	-1.58	1.55	-3.13	0.24	-3.72	3.96			
	[-0.94]	[-1.54]	[0.73]	[-0.53]	[0.76]	[-1.19]	[-0.65]	[0.58]	[-0.91]	[0.16]	[-1.40]	[1.38]			
B2. Shorted stocks															
	Short-sell	Cover	Difference	Short-sell	Cover	Difference	Short-sell	Cover	Difference	Short-sell	Cover	Difference	Short-sell	Cover	Difference
Underpriced	-0.10	5.48	-5.58	2.78	2.72	0.06	1.78	0.54	1.24	-1.74	1.30	-3.05	-0.66	4.33	-5.00
	[-0.04]	[2.78]	[-2.51]	[1.04]	[1.51]	[0.02]	[0.58]	[0.23]	[0.31]	[-0.53]	[0.59]	[-0.84]	[-0.17]	[2.24]	[-1.19]
Overpriced	-5.04	-0.49	-4.54	-4.97	-0.27	-4.70	-4.23	-1.31	-2.92	-1.49	-6.45	4.96	-7.29	0.68	-7.97
	[-2.31]	[-0.50]	[-2.06]	[-2.75]	[-0.32]	[-2.29]	[-1.61]	[-0.50]	[-0.96]	[-0.50]	[-1.79]	[1.24]	[-1.72]	[0.25]	[-1.77]

Table 8. Anomaly trading and performance of conditional anomaly portfolios in sub-periods

This table presents anomaly trading activity of alternative mutual funds (AMFs) and abnomal returns of anomaly portfolios conditional on AMFs' trading in Panels A and B, respectively, during the two sub-periods of 2002:7–2009:6 and 2009:7–2016:12. For each sub-period, we report the results averaged across the nine anomalies based on stocks held long and sold short by AMFs separately. In Panel A, We measure trading by Δ%Fund, defined as the change in fraction of AMFs over the six-quarter trading window prior to the anomaly portfolio formation date. In Panel B, we construct four value-weighted conditional anomaly portfolios by taking the intersection of the top and bottom 30% of the anomaly variable with the top and bottom 20% of Δ%Fund, and calculate annualized three-factor alphas (in percentage) of these portfolios. "Underpriced" ("Overpriced") refers to the top (bottom) 30% stocks ranked by the anomaly variable, and "Neutral" corresponds to the middle 40%. "Buy" ("Sell") and "Short-sell" ("Cover") refer to the top (bottom) 20% stocks ranked by Δ%Fund for those held long and sold short by AMFs, respectively. Figures in brackets are heteroskedasticity-adjusted t-statistics.

	Long stocks			Shorted stocks		
Panel A: Anomaly trading						
A1. 2002:7–2009:6						
	%Fund			%Fund		
Underpriced	51.77			17.96		
Neutral	46.47			20.76		
Overpriced	39.99			31.56		
U-N	5.31	[2.63]		-2.80	[-3.48]	
O-N	-6.48	[-4.25]		10.80	[11.71]	
U-O	11.79	[4.70]		-13.60	[-13.96]	
A2. 2009:7–2016:12						
	%Fund			%Fund		
Underpriced	25.99			9.81		
Neutral	22.78			10.36		
Overpriced	20.85			17.17		
U-N	3.21	[7.63]		-0.55	[-2.62]	
O-N	-1.93	[-5.56]		6.81	[5.16]	
U-O	5.14	[7.60]		-7.36	[-5.67]	
Panel B: Abnormal returns						
B1. 2002:7–2009:6						
	Buy	Sell	Difference	Short-sell	Cover	Difference
Underpriced	2.78	3.22	-0.44	-2.81	0.13	-2.94
	[1.47]	[1.20]	[-0.12]	[-1.06]	[0.06]	[-0.92]
Overpriced	0.98	0.94	0.05	-0.96	6.37	-7.33
	[0.32]	[0.21]	[0.01]	[-0.63]	[2.07]	[-2.81]
B2. 2009:7–2016:12						
	Buy	Sell	Difference	Short-sell	Cover	Difference
Underpriced	2.18	2.97	-0.79	-1.28	3.26	-4.53
	[0.92]	[1.86]	[-0.27]	[-0.50]	[2.76]	[-2.14]
Overpriced	-3.18	0.62	-3.80	-4.48	-1.36	-3.12
	[-1.49]	[0.32]	[-1.43]	[-2.52]	[-0.58]	[-2.17]