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Do sophisticated investors follow fundamental analysis strategies? Evidence from hedge funds and mutual funds

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Abstract
Using fund returns and fund stockholdings, we investigate whether fund managers follow fundamental analysis strategies. We show that hedge fund and mutual fund returns tend to load negatively on the long-short returns of a comprehensive sample of fundamental strategies (i.e., accounting anomalies), suggesting that fund managers are prone to trade in the opposite direction of what fundamental strategies prescribe. The negative loadings are primarily driven by the short-leg of the anomalies, more pronounced for contrarian-like anomalies, and more prevalent among earnings quality, investment, external financing, value, and profitability-based anomalies. We show that funds with higher anomaly loadings perform significantly better. Our results suggest that fund managers, as a group, do not systematically pursue fundamental analysis strategies, perhaps due to agency concerns, but a subset of managers are skilled and profit from employing such strategies. We find similar results when examining the stockholdings of hedge funds and mutual funds. Our findings have important implications for the persistence of accounting anomalies, sophistication of institutional investors, and investment value of fundamental analysis.

Keywords Fundamental analysis · Hedge funds · Mutual funds · Accounting anomalies

JEL Classification G11 · G12 · G23

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1 Introduction

Fundamental analysis attempts to separate winners and losers, that is, to identify mispriced stocks, on the basis of financial statement information that is not completely or perfectly impounded into prices. Consistent with this motivation, prior literature shows that many fundamental signals, including those based on earnings, cash flows, and accruals, predict the cross-section of stock returns (Richardson et al. 2010; Green et al. 2013). For example, Sloan (1996) finds that accruals are negatively associated with future stock returns. Abarbanell and Bushee (1998) show that the fundamental signals identified by Lev and Thiagarajan (1993), e.g., disproportionate inventory increase, provide significant information about future stock returns. Piotroski (2000) focuses on value stocks and shows that a long-short strategy based on the *F*-score, which captures the overall strength of a firm's financial position, generates significant abnormal returns. Overall, prior studies have documented considerable evidence that fundamental analysis works, and that it leads to profitable investment strategies.

In contrast to the extensive research on the profitability of fundamental analysis strategies, the question of whether sophisticated investors actually follow such strategies has received far less attention. This is surprising because the "principal motivation for fundamental analysis research and its use in practice is to identify mispriced securities for *investment* purposes" (Kothari 2001, p.171). Similarly, Richardson et al. (2010) contend that academic research on fundamental analysis has very direct applications and intellectual spillovers to actual investment practice. If fundamental strategies are profitable and the abnormal returns to these strategies result from inefficient prices (rather than compensations for systematic risk or data mining), then one would expect sophisticated investors, such as institutional investors, to actively follow fundamental strategies.

Several prior studies have investigated the issue and find mixed results. Ke and Ramalingegowda (2005) show that transient institutions exploit the post-earnings-announcement drift. Ali et al. (2008) find that few, if any, mutual funds trade on the accruals anomaly. Edelen et al. (2016) and Calluzzo et al. (2019) study stock market anomalies in general and include in their samples several accounting anomalies. Edelen et al. (2016) show that institutions trade contrary to anomaly prescriptions, whereas Calluzzo et al. (2019) find that institutional investors exploit market anomalies after they are published in academic journals. Most of the existing studies examine one or a small number of accounting anomalies and use the holdings data to infer institutional investors' trading behavior.[1] In this paper, we extend the existing literature in two ways.

First, instead of stockholdings, we primarily use fund returns to gauge the extent to which institutional investors pursue fundamental analysis strategies. Although stockholdings may inform us about institutional investors' trading behavior, such

[1] McLean et al. (2020) construct an index based on 130 market anomalies and investigate how nine different market participants, including institutional investors, trade with respect to this composite anomaly index. They do not examine individual anomalies or focus on accounting anomalies.

data (e.g., the 13F filings) have several limitations. Specifically, 13F filings do not include short positions, cannot capture intra-quarter trades, and are not mandatory for small institutions. Quarter-end stockholdings may also be distorted by window dressing. We overcome these limitations by examining fund returns. Intuitively, if fund managers employ fundamental strategies, i.e., buying underpriced stocks and selling overpriced stocks according to the predictions of the underlying fundamental signals, we would expect fund returns to be positively related to the long-short returns of fundamental strategies.

Second, in contrast to most prior studies that examine one or a few fundamental signals, we study a comprehensive sample of 54 fundamental strategies (i.e., accounting anomalies).[2] In particular, our sample includes a number of dedicated accounting anomalies that prior studies have largely overlooked. Examining a broad sample of anomalies allows us to draw more general conclusions on whether institutional investors trade on accounting anomalies and to answer the question of which accounting anomalies institutional investors tend to exploit. In addition, studying a comprehensive sample of accounting anomalies avoids the potential criticism of data snooping.

We focus on hedge funds and mutual funds in our analyses for three reasons. First, return data are readily available for hedge funds and mutual funds. Second, hedge funds and mutual funds are dominant players in the asset management industry. Third, hedge funds and mutual funds are widely considered as sophisticated investors who are likely to exploit market mispricing. Hedge funds, in particular, are regarded as the closest to the ideal rational arbitrageurs among all investors (Brunnemeier and Nagel 2004).

We begin our empirical analysis by examining whether hedge funds and mutual funds, in the aggregate, trade on accounting anomalies. We regress aggregate returns across all hedge funds or mutual funds on the long-short returns of each of the 54 accounting anomalies. We find that, on average, aggregate fund returns tend to load negatively on the long-short returns of accounting anomalies. For hedge funds, the loading is negative among 42 of the 54 anomalies and is positive for only 12 anomalies. Among the 42 negative loadings, 32 are statistically significant. The results for mutual funds are qualitatively similar—39 of the 54 loadings are negative (26 of which are statistically significant), while only 15 are positive.

Accounting anomalies are not independent from each other. For example, anomalies based on different variations and components of accruals (Sloan 1996) are closely related. We use a statistical clustering analysis to group our sample anomalies into the following categories: *Earnings Quality*, *Investment*, *Profitability*, *Profit Growth, External Financing, R&D*, and *Value*. We also create a separate category for several composite anomalies, namely *F*-score (Piotroski 2000), *G*-score (Mohanram 2005), updated *F*-scores (Piotroski and So 2012; Li and

[2] For ease of exposition, we use "fundamental analysis strategies", "fundamental strategies," and "accounting anomalies" interchangeably in this paper. Richardson et al. (2010) state that the research on fundamental analysis and the research on accounting anomalies significantly overlap, both having the primary goal of predicting earnings and returns.

Mohanram 2019), and *V/P* (Frankel and Lee 1998). Our results differ significantly across anomaly categories. Specifically, we find that the anomaly loadings are predominantly negative for the *Earnings Quality*, *Investment*, *Profitability, External Financing, Value,* and *Composite* categories. In contrast, for anomalies in the *Profit Growth* and *R&D* categories, the loadings are mostly positive.

Our results suggest that fund managers, as a group, do not systematically pursue fundamental analysis strategies. In fact, they appear to trade in the opposite direction of what most fundamental strategies prescribe. This finding is puzzling, particularly for hedge funds, which are considered among the most sophisticated investors. The negative anomaly loadings cannot simply be explained by traditional forms of limits to arbitrage (e.g., trading cost)—Shleifer and Vishny (1997) argue that constrained arbitrageurs should at least trade in the right direction.

A potential explanation for the negative anomaly loadings relates to the agency problem in professional money management. Lakonishok et al. (1994), for example, argue that the principal-agent conflict between the money managers and investors along with the short-term evaluation period may induce money managers to favor glamour stocks with superior past performance but poor subsequent performance. The agency explanation makes two additional testable predictions. First, the negative loadings should be concentrated in the short leg of the anomalies. This is because agency considerations primarily incentivize fund managers to hold overpriced, glamour stocks. To test this prediction, we regress fund returns on the returns of the long leg and short leg of each accounting anomaly separately. If fund managers exploit accounting anomalies in both long and short legs, we would expect fund returns to vary positively with the long-leg return and negatively with the short-leg return. Our results indicate that fund returns vary positively with the returns of both legs, especially the short leg, suggesting that fund managers bet in the wrong direction of accounting anomalies in the short leg.

The second prediction of the agency explanation is that the negative loadings should be more pronounced among contrarian-like anomalies than among momentum-like anomalies. This is because contrarian-like anomalies (e.g., the value anomaly) are driven by market overreaction, which causes glamour stocks to be overpriced. In contrast, momentum-like anomalies (e.g., the profit/loss anomaly of Balakrishnan et al. 2010) are driven by market underreaction, where overpricing occurs only among past underperforming companies. To test our prediction, we classify our sample accounting anomalies into momentum- and contrarian-like anomalies. We define momentum- (contrarian-) like anomalies as those whose holding period returns and formation period returns are in the same (opposite) direction. Our results indicate that the negative loadings are more prevalent among contrarian-like anomalies. Overall, our findings that the negative anomaly loadings are driven by the short-leg of the anomalies and are more pronounced among contrarian-like anomalies are consistent with the agency explanation.

Implementing fundamental analysis strategies incurs significant trading costs, particularly on the short side. Therefore, it is unclear whether hedge funds and mutual funds that trade on accounting anomalies can deliver superior performance after trading cost. To investigate this issue, we estimate anomaly loadings at the fund level and then link these loadings to fund performance. We find strong evidence that hedge funds and mutual funds with higher average anomaly loadings significantly outperform funds with lower average loadings. This result suggests that, even though most funds do not systematically pursue fundamental strategies, those funds that are sophisticated enough to do so exhibit superior fund performance.

In addition to fund returns, we also use stockholdings to examine whether institutions exploit accounting anomalies. We find no evidence that hedge funds and mutual funds tilt their portfolios towards profitable accounting anomaly factors. In fact, there is strong evidence that the stockholdings of hedge funds and mutual funds are weighted against most accounting anomalies, particularly among anomalies in the *Earnings Quality*, *Investment*, *External Financing*, and *Value* categories. These findings are broadly consistent with our results based on fund returns.

Our main contribution is to provide a first comprehensive study of whether institutional investors follow fundamental analysis strategies by using both fund returns and fund stockholdings.[3] We contribute to the literature in several specific ways. First, by examining fund returns, we provide an alternative perspective on the extent to which institutions pursue fundamental strategies. We argue that fund returns contain valuable incremental information about institutional investor trading behaviors relative to stockholdings. Second, instead of examining one or a few accounting anomalies, we study a comprehensive sample of 54 accounting anomalies including a number of prominent, dedicated fundamental analysis strategies that the previous literature has largely overlooked (e.g., *V/P* of Frankel and Lee 1998 and *G*-score of Mohanram 2005). Examining this broad sample of accounting anomalies also allows us to draw more general conclusions on whether sophisticated investors systematically exploit accounting anomalies. Third, to the best of our knowledge, we are the first to study which type of accounting anomalies that institutional investors tend to trade on. We show that the negative anomaly loadings are more pronounced among contrarian-like anomalies, and are more prevalent among earnings quality-, investment-, external financing-, profitability-, and value-based anomalies.

Our paper also contributes to several other streams of the accounting literature. We add to the literature examining the influence of institutional investors on the magnitude, persistence, and disappearance of accounting anomalies (e.g., Bartov et al. 2000; Collins et al. 2003; Green et al. 2011; Kokkonen and Suominen 2015). In particular, if mutual funds and hedge funds tend to trade contrary to the prescriptions of accounting anomalies, then these anomalies are likely to persist. Our paper also contributes to the extensive literature on whether institutional investors are informed (e.g., Ke and Petroni 2004; Bushee and Goodman 2007) by showing that fund managers do not systematically exploit accounting anomalies. Finally, we add to the recent accounting literature on meta-analysis of anomalies (e.g., Green et al. 2013; Chordia et al. 2014; Engelberg et al. 2020) by examining how mutual funds and hedge funds trade with respect to 54 accounting anomalies.

[3] Our approach is similar to Palhares and Richardson (2020), who examine both the returns and holdings of credit hedge funds and high-yield credit mutual funds to evaluate credit long–short managers' exposure to the credit risk premium.

Our paper is closely related to several finance studies that examine whether institutional investors exploit stock market anomalies. Edelen et al. (2016) show that institutions trade contrary to anomaly prescriptions, whereas Calluzzo et al. (2019) find that institutional investors exploit market anomalies after they are published in academic journals. McLean et al. (2020) investigate how nine different market participants including institutional investors trade with respect to a composite anomaly index constructed based on 130 market anomalies. They find evidence consistent with both Edelen et al. (2016) and Calluzzo et al. (2019) among certain types of institutions. Our paper differs from the above studies in at least two ways. First, we focus on accounting anomalies and classify them into different categories based on a clustering analysis. Second, we primarily use fund returns to gauge the extent to which institutional investors exploit accounting anomalies.

The rest of the paper proceeds as follows. Section 2 discusses the related literature. Section 3 describes the data, sample, and summary statistics. Section 4 presents the empirical results. Section 5 concludes.

2 Related literature and hypothesis development

2.1 Related literature

Fundamental analysis attempts to separate ex-post winners and losers based on financial statement information that is not perfectly impounded into prices. For example, Kothari (2001) note that a primary focus of fundamental analysis research is to identify mispriced securities relative to their intrinsic values for investment purposes. To this end, most of the fundamental analysis research in accounting aims to develop better forecasts of earnings or stock returns, which help with the valuation and identification of mispriced securities.

Lev and Thiagarajan (1993) identify 12 fundamental signals used by professional financial analysts including, e.g., disproportionate growth in inventory, disproportionate growth in accounts receivables, and gross margin rate. Lev and Thiagarajan demonstrate the value relevance of these signals by showing that they are significantly associated with contemporaneous stock returns in the predicted direction. Abarbanell and Bushee (1997) further demonstrate that these fundamental signals' association with contemporaneous returns can be explained by their ability to predict future earnings—an underlying premise of fundamental analysis.

A common theme in fundamental analysis research is to examine whether the application of fundamental analysis can generate significant above-normal investment returns. This question is motivated by the extensive evidence in the accounting and finance literatures that stock prices often fail to immediately reflect publicly available information. Abarbanell and Bushee (1998), for example, devise an investment strategy based on the fundamental signals identified by Lev and Thiagarajan (1993) and show that the strategy yields significant abnormal returns.

Piotroski (2000) focuses on value stocks and applies standard financial statement analysis to this subset of stocks. He constructs an *F*-score based on a firm's profitability, financial leverage and liquidity, and operating efficiency, and shows that the *F*-score has strong predictive power for future returns. Mohanram (2005) extends Piotroski's (2000) approach to growth stocks. He creates a *G*-score based on traditional fundamental measures as well as measures tailored to growth firms, such as earnings stability, growth stability, and R&D intensity, capital expenditure and advertising. Mohanram (2005) shows that a long-short strategy based on *G*-score earns significant excess returns. Piotroski and So (2012) and Li and Mohanram (2019) expand the analyses of Piotroski (2000) and Mohanram (2005) and demonstrate that combining *F*-score with value strategies substantially improves the efficacy of fundamental analysis.

Several studies use a statistical approach to identify fundamental signals that predict future earnings and stock returns. Ou and Penman (1989) examine an exhaustive list of accounting ratios and extract a summary measure that predicts the direction of future earnings and future stock returns. Yan and Zheng (2017) construct a universe of fundamental signals using permutational arguments and show that many fundamental signals are significant predictors of the cross-section of stock returns, even after accounting for the influence of data mining. Bartram and Grinblatt (2018) take the view of a statistician and find that a basic form of fundamental analysis yields significant risk-adjusted returns.

While the majority of fundamental analysis research focuses on identifying fundamental signals that indicate deviations from fair value, Frankel and Lee (1998) and Lee et al. (1999) directly estimate fundamental value by using the residual income model (Ohlson 1995) combined with analysts' forecasts. They show that the ratio of estimated fundamental value to price predicts the cross section of stock returns, and that investing in mispriced stocks based on the estimated fundamental values earns significant abnormal returns. Overall, prior studies based on both accounting ratios and estimated intrinsic values have documented ample evidence that fundamental analysis works, and that it yields profitable investment strategies.

Competing explanations for the profitability of fundamental strategies fall into two categories. Behavioral explanations suggest that the return predictability represents market inefficiency and arises because the stock prices fail to fully reflect available information. Alternatively, rational explanations suggest that the abnormal returns are compensations for bearing risk that is priced but not captured by traditional asset pricing models. Most prior studies find evidence consistent with behavioral explanations. For example, Bernard and Thomas (1989, 1990) present evidence suggesting that the post-earnings-announcement-drift (PEAD) is due to naïve investors' failure to recognize the implications of current earnings for future earnings. Sloan (1996) shows that the accruals anomaly arises because the market does not understand the difference in persistence of the cash flow and accrual components of the earnings. Bernard et al. (1997) examine whether six accounting-based anomalies represent market mispricing or risk premia and find mixed results. Khan (2008) presents a risk-based explanation for the accruals anomaly.

If the abnormal returns to fundamental strategies are due to market inefficiency, then one would expect sophisticated investors such as institutional investors to arbitrage against the mispricing by actively following fundamental strategies. Several studies have investigated the issue and find mixed results. Ke and Ramalingegowda

(2005) find that transient institutions exploit PEAD and their trading speeds up the incorporation of earnings information into prices. Ali et al. (2008) find that few actively managed mutual funds trade on the accruals anomaly. To date, there is no comprehensive study on whether institutional investors systematically follow fundamental analysis strategies.

A number of finance papers examine whether institutional investors exploit market anomalies in general. For example, Griffin and Xu (2009) examine the stockholdings of hedge funds and show that hedge funds exhibit little ability to pick stock styles. Lewellen (2011) shows that institutional investors as a whole essentially hold the market portfolio, not betting on any of the well-known stock return anomalies. Akbas et al. (2015) show that mutual fund flows aggravate cross-sectional return anomalies, while hedge fund flows attenuate mispricing. Edelen et al. (2016) examine seven anomalies and find that institutions have a strong tendency to buy stocks classified as overvalued (short leg of anomaly) during the anomaly formation period. In contrast, Calluzzo et al. (2019) examine 14 market anomalies and show that institutional investors do trade on them during post-formation period, but only after they are published in academic journals. McLean et al. (2020) perform a comprehensive analysis of how different market participants including institutional investors trade with respect to a composite anomaly index constructed based on 130 market anomalies. They find evidence consistent with both Edelen et al. (2016) and Calluzzo et al. (2019) among certain types of institutions. All of the above finance studies use stockholdings to infer institutional investor trading behaviors and do not focus on accounting anomalies.

2.2 Hypothesis development

If hedge funds and mutual funds are sophisticated and exploit the return predictability associated with fundamental signals, they will buy stocks that are relatively undervalued (e.g., stocks with low accruals) and sell stocks that are relatively overvalued (e.g., stocks with high accruals). As such, their returns will be positively correlated with the long-short returns of accounting anomalies.

H1: Hedge fund and mutual fund returns load positively on the long-short returns of accounting anomalies.

Trading on accounting anomalies incurs significant trading costs. If the benefits of trading on accounting anomalies outweigh the costs, we expect hedge funds and mutual funds that trade on accounting anomalies to perform better than those that do not.

H2: Funds with higher anomaly loadings exhibit better performance.

In addition to fund returns, we also use the stockholdings of mutual funds and hedge funds to examine whether they exploit accounting anomalies.

H3: Compared to their benchmark portfolios, hedge funds and mutual funds overweight stocks that are relatively undervalued and underweight stocks that are relatively overvalued.

3 Data, sample, and descriptive statistics

3.1 Fundamental analysis strategies

To compile a comprehensive sample of fundamental analysis strategies or accounting anomalies, we start with the samples of anomalies from Green et al. (2013), Hou et al. (2015), and McLean and Pontiff (2016). Next we restrict our sample to anomaly variables that can be constructed primarily using the Compustat data. In addition, we add to our sample several dedicated accounting anomalies not included in the above-mentioned studies. Our final sample includes 54 accounting anomalies. The appendix contains the detailed definitions and citation sources of these 54 anomalies.

To construct these accounting anomalies, we obtain stock data including return, share price, SIC code, and shares outstanding from the Center for Research in Security Prices (CRSP), analyst earnings forecasts from I/B/E/S, and quarterly and annual accounting data from Compustat. Our sample consists of common stocks (with a CRSP share code of 10 or 11) traded on NYSE, AMEX, and NASDAQ and with data necessary to compute the anomaly variables and subsequent stock returns. We exclude financial stocks and stocks with a price lower than $5 at the portfolio formation date. We also remove stocks whose market capitalization is ranked in the lowest NYSE decile at the portfolio formation date. We remove low-priced and micro-cap stocks to ensure that our results are not driven by small and illiquid stocks.

To construct anomaly portfolios, we sort all sample stocks into deciles based on each anomaly variable and form equal- and value-weighted portfolios. We examine the strategy that goes long on stocks in the top decile and short those stocks in the bottom decile, where the top (bottom) decile contains the stocks that are expected to outperform (underperform) based on prior literature. Taking the accruals anomaly as an example, we long stocks in the lowest-accrual decile and short stocks in the highest-accrual decile because prior studies (e.g., Sloan 1996) have shown that accrual is a negative predictor of the cross-section of stock returns.

We form anomaly portfolios every month by using the most recently available financial statement information. This means we use the latest quarterly data whenever available, even if the anomalies were constructed based on annual data in the original studies. Specifically, for balance sheet variables, such as total assets, we simply use the data at the end of the most recent fiscal quarter, rather than the end of the most recent fiscal year. For income statement variables, such as sales, we sum over the variable during the most recent four quarters. When quarterly data are not available (e.g., advertising), we continue to use the annual Compustat data. To ensure that investors have access to the accounting data when forming portfolios, we assume that the annual Compustat data are available three months after the fiscal year-end and the quarterly Compustat data are available two months after the fiscal quarter-end.

Accounting anomalies are not independent from each other. For example, anomalies based on different variations and components of accruals (Sloan 1996) are closely related. We follow Jensen et al. (2022) and group our sample anomalies into clusters by using the hierarchical agglomerative clustering approach of Murtagh and Legendre (2014). Similar to Jensen et al. (2022), we define the distance between anomalies as one minus the pairwise correlation in their long-short returns and use the linkage criterion of Ward (1963). Based on the results of this clustering analysis, we choose the following seven clusters that demonstrate a high degree of economic and statistical similarity: *Earnings Quality*, *Investment*, *Profitability*, *Profit Growth, External Financing, R&D*, and *Value,* where the cluster names indicate the types of accounting characteristics that dominate each group. In addition, we create a separate category for several composite anomalies, namely *F*-score (Piotroski 2000), *G*-score (Mohanram 2005), updated *F*-scores (Piotroski and So 2012; Li and Mohanram 2019), and *V/P* (Frankel and Lee 1998). For brevity, we refer the readers to the appendix for details of the eight anomaly categories and their constituent anomalies.

3.2 Hedge fund and mutual fund data

We obtain hedge fund data from Lipper TASS, one of the most widely used hedge fund databases in the academic literature. The Lipper TASS database contains both live funds and defunct funds. We obtain monthly hedge fund returns and various fund characteristics including fund assets under management, minimum investment, fee structure, the use of high-water mark, leverage, and share restriction provisions. The sample period for our hedge fund data is 1994–2020. We begin our sample in 1994 because data prior to 1994 are subject to a survivorship bias (Fung and Hsieh 1997; Liang 2000).

Following the previous literature, we mitigate the backfilling bias in the hedge fund data by removing the first 12 months' observations for each fund from the sample (e.g., Teo 2011). We also exclude funds before their assets under management exceed $10 million. In addition, we only consider funds that report net returns on a monthly basis in U.S. dollars. We keep both live and defunct funds in the sample to remove survivorship bias. Our final sample contains 6,056 hedge funds. We obtain Fung and Hsieh (2004) seven factors from David Hsieh's website.[4]

We obtain monthly mutual fund returns, total net assets (TNA), expense ratio, turnover rate, and other fund characteristics from the CRSP Survivor-Bias-Free Mutual Fund Database. For ease of comparison with hedge funds, our sample period for mutual funds is also 1994–2020. Many funds have multiple share classes, which typically differ only in fee structure (expense ratio, 12b-1 fee, and load charges).

[4] https://faculty.fuqua.duke.edu/~dah7/HFData.htm.

We combine these different share classes into a single fund. In particular, we calculate the TNA of each fund as the sum of the TNA of each share class and calculate fund age as the age of its oldest share class. For all other fund characteristics, e.g., expense ratio, we use the TNA-weighted average across all share classes.

We limit our analysis to U.S. domestic actively managed equity mutual funds. We follow the procedures of Doshi et al. (2015) and rely on the CRSP investment object code to identify such funds. We exclude international, balanced, sector, bond, money market, and index funds from our sample. We also exclude funds that have less than 80% of their holdings in common stocks.

To mitigate the effect of incubation bias, we include a fund only after its TNA has surpassed \$15 million. Once a fund enters our sample, we do not exclude it even if its TNA drops below \$15 million. We further exclude observations prior to the first offer date of the fund (i.e., the date of organization) to reduce incubation bias. We require a minimum of 12 monthly returns for a fund to be included in our sample. Our final sample includes 2,947 distinct mutual funds.

We obtain mutual fund stockholdings from the Thomson Reuters Mutual Fund Holdings Database. We obtain hedge funds' quarterly stock holdings by merging TASS with the Thomson Reuters 13F database. In the United States, institutions with over \$100 million of assets under management need to report their quarter-end stock positions that are over 10,000 shares or worth more than \$200,000. Following Griffin and Xu (2009) and Cao et al. (2018), we identify hedge fund companies in the 13F database by manually matching the institutional investors' names from 13F with the asset management companies' names from Lipper TASS. To ensure accuracy, we require exact match of the names. Note that the hedge fund holdings are at the hedge fund company level rather than the fund level.

3.3 Summary statistics

We present the summary statistics of our sample funds in Table 1. Panel A presents the results for hedge funds. We find that the average total asset under management (AUM) of our sample hedge funds is \$160.32 million. The average hedge fund requires a minimum investment of \$1.35 million from its investors and charges a 1.39% management fee and a 15.03% incentive fee. The average Fung and Hsieh (2004) seven-factor alpha for our sample hedge funds is 10 basis points per month, consistent with the existing evidence that hedge funds tend to exhibit positive abnormal returns. (See Agarwal et al. 2015 for a review of the hedge fund performance literature.)

Panel B presents the summary statistics of our sample mutual funds. The average total net assets under management (TNA) is \$728.76 million. The average fund is over nine years old and has an expense ratio of 1.23% and a turnover rate of 87.54% per year. The average total load (front-end load plus back-end load) is 1.01%. The average Capital Asset Pricing Model (CAPM) alpha for our sample mutual funds is -14 basis points per month, consistent with evidence that actively managed mutual funds underperform the market after fees (e.g., Wermers 2000).

As noted earlier, we group the 54 accounting anomalies into eight categories: *Earnings Quality*, *Investment*, *Profitability*, *Profit Growth*, *External Financing*,

Table 1 Summary statistics of sample hedge funds and mutual funds

Panel A: Hedge Fund				
	Mean	Median	P10	P90
Fund_AUM ($ million)	160.32	48.00	11.57	342.13
Fund_Age (month)	64.52	50.13	20.25	125.00
Management Fee (%)	1.39	1.50	1.00	2.00
Incentive Fee (%)	15.03	20.00	0.00	20.00
Minimum Investment ($ million)	1.35	0.50	0.05	1.00
Lock-up	0.28	0.00	0.00	1.00
Lock-up Period (month)	3.65	0.00	0.00	12.00
Redemption Notice Period (day)	40.90	30.00	0.00	90.00
HWM	0.65	1.00	0.00	1.00
Personal Capital	0.27	0.00	0.00	1.00
Leveraged	0.54	1.00	0.00	1.00
Alpha (% per month)	0.10	0.13	-0.81	0.87
Panel B: Mutual Fund				
	Mean	Median	P10	P90
Fund_AUM ($ million)	728.76	169.71	22.62	1,512.16
Fund_Age (month)	111.68	91.57	33.67	193.61
Turn_ratio (%)	87.54	70.77	25.94	154.49
Exp_ratio (%)	1.23	1.19	0.76	1.79
Load (%)	1.01	0.13	0.00	2.75
Alpha (% per month)	-0.14	-0.10	-0.50	0.16

This table reports summary statistics of sample fund characteristics. Hedge fund data are from the Lipper TASS database. We remove the first 12 months of observations for each fund. We also remove all observations before a fund reaches $10 million in total net assets. We only retain funds that invest in equity markets and report net returns on a monthly basis in U.S. dollars. Mutual fund data are from the CRSP Mutual Fund Database. We combine different share classes of the same fund into a single fund. We restrict our analysis to U.S. domestic actively managed equity mutual funds. In particular, we exclude international, balanced, sector, bond, money market, and index funds from our sample. We also exclude funds that have less than 80% of their holdings in common stocks. We include a fund only after its TNA has surpassed $15 million. We also exclude observations prior to the first offer date of the fund. Our final sample include 6,056 hedge funds and 2,947 mutual funds. The sample period is 1994–2020. Alpha is Fung and Hsieh (2004) seven-factor alpha for hedge funds, and is CAPM alpha for mutual funds

R&D, *Value*, and *Composite*. Given that these categories are formed based on statistical similarity, we expect the correlations among anomalies within the same category to be significantly higher than the correlations among anomalies across different categories. As stated earlier, we calculate the correlations between anomalies by using their long-short returns. Table 2 presents the correlation matrix for the eight anomaly categories. The numbers on the diagonal represent the average (or median) within-category correlations, while the numbers on the off-diagonal represent the across-category correlations. Specifically, for each category, e.g., *Investment*, we first compute the pairwise correlations among all anomalies in the *Investment* category and then report the average and median of these correlations. This is the within-category correlation. For the cross-category correlation, e.g., between

Investment and *Profitability*, we first compute the pairwise correlation between all anomalies in the *Investment* category and all anomalies in the *Profitability* category and then report the average and median of these correlations. To facilitate a comparison between within-category correlations and cross-category correlations, we also report in the last row of Table 2 the average cross-category correlations between a particular category and all other seven categories.

Consistent with our expectation, we find that within-category correlations are considerably larger than cross-category correlations. For example, the average correlation among all value anomalies is 0.71. In comparison, the correlations between value anomalies and anomalies in the other categories range from -0.33 to 0.48, with an average of 0.13. In another example, the average correlation among all profitability anomalies is 0.57. In comparison, the correlations between profitability anomalies and anomalies in other categories range from -0.23 to 0.45, with an average of 0.16.

4 Empirical results

4.1 Anomaly loadings

We begin our empirical analysis by examining whether, in the aggregate, fund returns load positively on anomaly returns. We first calculate the average return across all hedge funds or mutual funds in each month.[5] We then estimate a time-series regression of aggregate hedge fund or mutual fund returns on the long-short returns of each of the 54 accounting anomalies while controlling for standard risk factors.

$$r_t = \alpha + \beta LS_t + \boldsymbol{\theta'}\mathbf{X}_t + e_t \tag{1}$$

where r_t is the aggregate hedge fund or mutual fund return in month t; LS_t is the value-weighted long-short return of the accounting anomaly in month t; and $\mathbf{X}_t$ is a vector of control variables that include the Fung and Hsieh (2004) seven factors for hedge funds and the market factor for mutual funds.[6] As stated earlier, if fund managers trade on accounting anomalies, we would expect fund returns to vary positively with the long-short returns of accounting anomalies. That is, we expect β to be significantly positive. We also estimate separate regressions for the long and short legs of the anomaly as follows:

$$r_t = \alpha_L + \beta_L Long_t + \boldsymbol{\theta}'_L\mathbf{X}_t + e_t \tag{2}$$

$$r_t = \alpha_S + \beta_S Short_t + \boldsymbol{\theta}'_S\mathbf{X}_t + e_t \tag{3}$$

where $Long_t$ and $Short_t$ are the returns to the long and short legs of the accounting anomaly, respectively. If fund managers exploit accounting anomalies in both long

[5] Our results are qualitatively similar if we compute total net assets (TNA)-weighted average returns across all hedge funds or mutual funds. See Table IA.1 in the Internet Appendix for details.

[6] Our results are similar if we control for Fama and French three factors instead of the market factor in the regression of mutual fund returns.

Table 2 Correlation matrix

	Earnings quality	Investment	Profitability	Profit growth	External financing	R&D	Value	Composite
Earnings Quality	**0.36**							
	(0.32)							
Investment	0.27	**0.28**						
	(0.29)	(0.28)						
Profitability	0.12	0.09	**0.57**					
	(0.12)	(0.11)	(0.56)					
Profit Growth	-0.12	-0.02	0.11	**0.21**				
	(-0.12)	(-0.03)	(0.10)	(0.22)				
External Financing	0.31	0.20	0.45	-0.06	**0.59**			
	(0.29)	(0.26)	(0.49)	(-0.07)	(0.59)			
R&D	-0.15	-0.07	-0.23	0.02	-0.40	**0.37**		
	(-0.10)	(-0.11)	(-0.24)	(-0.02)	(-0.45)	(0.39)		
Value	0.31	0.12	0.21	-0.18	0.48	-0.33	**0.71**	
	(0.32)	(0.18)	(0.23)	(-0.19)	(0.48)	(-0.46)	(0.69)	
Composite	0.13	0.07	0.41	0.05	0.41	-0.28	0.34	**0.34**
	(0.12)	(0.09)	(0.42)	(0.05)	(0.41)	(-0.30)	(0.36)	(0.34)
Average with all other categories	**0.12**	**0.09**	**0.16**	**-0.03**	**0.20**	**-0.21**	**0.13**	**0.16**

This table reports the average long-short return correlations between anomalies within the same anomaly category or across different categories. Our sample of 54 anomalies is compiled from Green et al. (2013), Hou et al. (2015), and McLean and Pontiff (2016). The detailed list and definitions of these 54 anomalies are contained in the Appendix. We obtain monthly stock data from the CRSP, accounting data from Compustat, and analyst forecast data from I/B/E/S. Our sample period is from 1994 to 2020. For each anomaly variable, we construct long-short strategies based on the two extreme deciles, with the long position being the higher-performing decile and the short position being the lower-performing decile (according to prior literature). We group our sample anomalies by using the agglomerative clustering approach (Jensen et al. 2022; Murtagh and Legendre 2014). The diagonal terms are the average pairwise Pearson correlations between anomalies within the same category. The off-diagonal terms are the average correlations between anomalies across different categories. Median correlations are shown in the parentheses. The last row shows the average correlation of anomalies in each category with anomalies in the other seven categories and short legs, we would expect fund returns to vary positively with the long-leg return and negatively with the short-leg return of accounting anomalies. That is, we expect β_L to be positive and β_S to be negative.

We present the results in Table 3. For brevity, we only tabulate the results on anomaly loadings (i.e., the β s). We organize the results by anomaly categories (described in Sect. 3.1), with one category in each panel. For each anomaly, we first present the overall anomaly loading (β) and then the loadings for the long leg (β_L) and the short leg (β_S). We report the results separately for hedge funds and mutual funds.

In addition to anomaly loadings, we also report the CAPM alphas of the 54 accounting anomalies in Table 3.[7] We find that the majority of the accounting anomalies in our sample exhibit positive and significant CAPM alphas during our sample period. Specifically, the equal-weighted CAPM alpha is positive among 51 of the 54 anomalies, 40 of which are statistically significant. The value-weighted CAPM alpha is positive among 49 of the 54 anomalies and 31 of them are statistically significant.

Next, we turn our attention to anomaly loadings. We find that aggregate fund returns tend to load negatively on anomaly returns. For hedge funds, the anomaly loading is negative among 42 of the 54 accounting anomalies, and is positive for only 12 anomalies. Out of the 42 negative loadings, 32 are statistically significant at the 10 percent level or better. The results for mutual funds are qualitatively similar. Specifically, we find that 39 of the 54 anomaly loadings are negative (26 of which are statistically significant), while only 15 are positive.

Our results differ significantly across anomaly categories. Specifically, we find that the anomaly loadings are predominantly negative among anomalies in the *Earnings Quality*, *Investment*, *Profitability, External Financing, Value,* and *Composite* categories. For example, the anomaly loading is negative among all 10 anomalies in the *Earnings Quality* category for hedge funds, and nine out of 10 for mutual funds. Similarly, the anomaly loading is negative among six out of seven anomalies in the *Investment* category for both hedge funds and mutual funds. We also note that, for both hedge funds and mutual funds, four out of five of the composite anomalies exhibit negative loadings. In contrast, for anomalies in the *Profit Growth* and *R&D* categories, the loadings are mostly positive. For example, the anomaly loading is positive among seven out of nine anomalies in the *Profit Growth* category for hedge funds, and five out of nine for mutual funds.

Examining our results at the anomaly category level is important because, as noted earlier, accounting anomalies are not independent. For example, even though there are 10 anomalies in the *Earnings Quality* category, they are correlated with each other. Therefore, we cannot treat them as ten independent observations. Viewing our results at the anomaly category level mitigates this concern. We show that the anomaly loading is predominantly negative among six of the eight categories, and is positive in two categories, so our finding that fund returns tend to load negatively on the long-short returns of accounting anomalies continues to hold when viewed at the anomaly category level.

[7] We report CAPM alphas because accounting anomalies are traditionally identified as return patterns that cannot be explained by the CAPM.

Table 3 Aggregate hedge fund and mutual fund loadings on anomaly returns

Panel A: Earnings Quality

Anomaly	CAPM α		Hedge Funds			Mutual Funds		
	EW	VW	Hedge	Long	Short	Hedge	Long	Short
TAcc	0.79***	0.54***	-0.04***	0.05**	0.07***	-0.04***	0.06***	0.08****
PTAcc	0.70****	0.58***	-0.05***	0.07**	0.11****	-0.02	0.14****	0.13****
OAcc	0.37***	0.44**	-0.02	0.04**	0.07***	-0.06***	0.04**	0.14****
POAcc	0.57***	0.70***	-0.00	0.06***	0.05**	-0.03**	0.09***	0.13****
AG	0.80***	0.42	-0.04***	-0.02	0.06****	-0.03***	0.08***	0.07****
BrandCap	0.03	0.10	-0.02	0.03**	0.04***	-0.01	-0.02	0.01
dSales	0.37*	0.38	-0.05***	0.00	0.08****	-0.03***	0.07***	0.10****
dBE	0.43***	0.24	-0.04***	0.06**	0.07***	-0.03**	0.12***	0.08****
dOA	1.04***	0.49**	-0.06***	0.03	0.09****	-0.05***	0.04	0.09****
dNCOA	0.32***	0.02	-0.07***	-0.05	0.20***	0.07***	-0.07**	-0.40****

Panel B: Investment

Anomaly	CAPM α		Hedge Funds			Mutual Funds		
	EW	VW	Hedge	Long	Short	Hedge	Long	Short
CI	0.55***	0.64***	0.00	0.08***	0.11****	0.01	0.11****	0.16****
I/A	0.95****	0.24	-0.07***	0.04	0.12****	-0.04***	0.12***	0.12****
dInv	0.47***	0.62***	-0.05***	0.03	0.08****	-0.02*	0.14****	0.12****
dInv_adj	0.61***	0.69***	-0.03*	0.09***	0.07***	-0.01	0.15****	0.09****
IG	0.67***	0.46**	-0.04***	0.07***	0.09****	-0.06****	0.06***	0.12****
dInvent	0.68***	0.43*	-0.02*	0.02	0.06***	-0.02	0.13****	0.13****
NOA	1.02***	0.88***	-0.01	0.06***	0.11****	-0.01	0.06***	0.13****

Table 3 (continued)

Panel C: Profitability

Anomaly	CAPM α		Hedge Funds			Mutual Funds		
	EW	VW	Hedge	Long	Short	Hedge	Long	Short
ROA	1.04***	1.11***	-0.03**	0.08***	0.05***	-0.06****	-0.04*	0.07****
ROE	1.08***	1.05***	-0.04***	0.05*	0.06***	-0.07****	-0.11***	0.08****
RNOA	0.91***	1.20***	-0.02*	0.09***	0.04***	-0.08****	-0.00	0.08****
GP/A	1.05***	0.91***	-0.03***	-0.05**	0.03**	-0.02**	0.00	0.03**
Cturn	0.49**	0.48**	-0.01	0.01	0.04**	-0.00	0.02	0.02
OrgCap	0.68***	1.04***	-0.08****	-0.10***	0.10****	-0.05***	0.03	0.10****
OperLev	0.61***	0.57***	-0.04***	-0.02	0.07***	0.01	-0.00	-0.02
PM	0.99***	1.16***	-0.03***	0.10***	0.04***	-0.08****	-0.18****	0.07****

Panel D: Profit Growth

Anomaly	CAPM α		Hedge Funds			Mutual Funds		
	EW	VW	Hedge	Long	Short	Hedge	Long	Short
SUE	0.54***	0.48**	-0.00	0.01	0.01	-0.01	-0.07***	-0.04*
RS	0.70***	0.64***	0.01	0.05**	0.02	-0.03**	-0.01	0.07***
TaxExp	0.48***	0.26	0.04***	0.08****	0.04*	0.02	0.06***	0.05**
EAR	1.22****	0.88***	0.06***	0.08****	0.01	0.04***	0.09****	0.06***
SA_SGA	-0.04	0.07	0.04***	0.11****	0.05**	0.02	0.08****	0.05***
SA_IV	0.21*	0.34*	-0.01	0.08***	0.09***	-0.04***	0.05***	0.12****
dNWC	0.12	0.14	0.04	0.16***	0.08*	-0.05*	-0.28****	-0.22****
dAturn	-0.14	-0.08	0.01	0.06***	0.03**	0.03**	0.10****	0.04***
dPM	0.32**	0.26	0.02*	0.07****	0.05***	0.02***	0.09****	0.06***

Table 3 (continued)

Panel E: External Financing								
Anomaly	CAPM α		Hedge Funds			Mutual Funds		
	EW	VW	Hedge	Long	Short	Hedge	Long	Short
Xfin	1.19***	1.01***	-0.05***	-0.00	0.05***	-0.09****	-0.15****	0.10****
NSI	1.03***	0.55***	-0.06***	0.01	0.11****	-0.11****	-0.03	0.16****
Payout	0.32	0.21	-0.05****	-0.06**	0.08****	-0.04***	0.04*	0.11****
Npayout	0.87***	0.80***	-0.07****	-0.07***	0.11****	-0.07****	0.01	0.15****
TI/BI	0.28*	0.34*	-0.01	0.12****	0.09***	-0.05***	0.07**	0.12****

Panel F: R&D								
Anomaly	CAPM α		Hedge Funds			Mutual Funds		
	EW	VW	Hedge	Long	Short	Hedge	Long	Short
R&D/A	0.30	0.50	0.03***	0.04***	0.04*	0.05****	0.06****	-0.06***
R&D/M	0.59**	0.28	-0.01	0.03**	0.09***	0.05****	0.07****	-0.01
Aturn	0.41**	0.56**	0.02*	0.04***	0.02	0.03**	0.04***	-0.01
AccQ	-0.45*	-0.33	0.03**	0.04***	-0.03	0.06****	0.07***	-0.09***

Panel G: Value								
Anomaly	CAPM α		Hedge Funds			Mutual Funds		
	EW	VW	Hedge	Long	Short	Hedge	Long	Short
E/P	0.30	0.21	-0.02*	0.04**	0.07***	-0.02	0.06***	0.10****
CF/P	0.19	-0.12	-0.02**	0.03*	0.07****	-0.01	0.06***	0.06***
B/M	0.10	-0.25	-0.05****	-0.06***	0.09****	-0.00	0.02	0.03*
A/M	0.09	-0.28	-0.04***	-0.07***	0.07***	-0.00	0.03*	0.03**
S/P	0.66	0.14	-0.03***	-0.05***	0.04***	0.00	0.08****	0.04***
AD/M	0.58	0.49	-0.03***	-0.07***	0.03***	0.00	0.05***	0.03***

Table 3 (continued)

Panel H: Composite

Anomaly	CAPM α		Hedge Funds			Mutual Funds		
	EW	VW	Hedge	Long	Short	Hedge	Long	Short
F-score	0.49 **	0.42 *	-0.00	0.07 ***	0.08 ***	-0.02	0.10 ****	0.13 ****
G-score	0.96 ****	0.75 ***	-0.06 ***	0.05	0.07 ***	-0.12 ****	-0.34 ****	0.12 ****
PS	0.86 **	0.57	-0.02 **	-0.02	0.03 **	-0.03 ***	0.04 **	0.07 ****
LM	0.71 **	0.37	-0.02 **	0.02	0.05 ***	0.01	0.09 ****	0.05 ***
V/P	0.38	0.66 **	0.03 ***	0.09 ****	0.03 ***	-0.00	0.06 ***	0.07 ****

This table reports hedge fund or mutual fund aggregate loadings on anomalies and the CAPM α for our sample accounting anomalies. The detailed list and definitions of 54 anomalies are contained in the Appendix. Our sample period is from 1994 to 2020. We group our sample anomalies by using the agglomerative clustering approach (Jensen et al. 2022; Murtagh and Legendre 2014) and organize our panels by anomaly category. For each anomaly variable, we construct long-short portfolios with the long position being the higher-performing decile and the short position being the lower-performing decile (according to prior literature). We compute CAPM alphas (expressed in percent per month) by regressing anomaly returns on the market factor. Hedge fund data are obtained from the Lipper TASS database, and mutual fund data are obtained from CRSP mutual fund database. Our final sample include 6,056 hedge funds and 2,947 mutual funds. We first compute hedge fund or mutual fund equal-weighted aggregate returns and then regress the aggregate returns on the time series of anomaly returns. We also regress the aggregate fund returns on the long leg and the short leg of anomalies separately. We adjust t-statistics for heteroscedasticity and autocorrelations and use *, **, *** and **** for $|t\text{-stats}| \geq 1.65$, $|t\text{-stats}| \geq 1.96$, $|t\text{-stats}| \geq 2.58$ and $|t\text{-stats}| \geq 5$, respectively

To more clearly show how our results differ across anomaly categories, we plot in Fig. 1 the number of anomalies with positive or negative loadings in each anomaly category. Figure 1 shows that the hedge funds' anomaly loading is negative among all anomalies in the *Earnings Quality*, *External Financing*, *Value*, and *Profitability* categories, predominantly negative for the *Investment* and *Composite* categories, and mostly positive for the *Profit Growth* and *R&D* categories. The chart for mutual funds follows a similar pattern.

Next, we examine whether the negative loadings on anomaly returns are driven by the long leg or short leg of the anomalies. As stated earlier, if fund managers exploit accounting anomalies in both the long leg and the short leg, then we would expect the loading on the long leg to be positive and the loading on the short leg to be negative. The results in Table 3 indicate that fund returns tend to load positively on both the long and short legs, especially the short leg. Specifically, for the long leg, both hedge fund returns and mutual fund returns exhibit positive loadings among 41 of the 54 accounting anomalies. For the short leg, the number of positive loadings is 53 for hedge funds and 46 for mutual funds. These results suggest that fund managers on average exploit accounting anomalies in the long leg but fail to do so in the short leg. Instead of underweighting stocks in the short leg, fund managers appear to overweight these stocks in their portfolios.Overall, our results indicate that the negative anomaly loadings are primarily driven by the short leg of the anomalies.

4.2 Agency explanation

The negative anomaly loadings indicate that fund managers, as a group, do not systematically exploit the return predictability of accounting information. In fact, they appear to trade contrary to the predictions of accounting anomalies. This finding is puzzling and cannot simply be explained by traditional forms of limits to arbitrage, such as trading cost and idiosyncratic volatility, because Shleifer and Vishny (1997) argue that arbitrageurs, even when constrained, should at least trade in the right direction.

Our results appear to be consistent with the theoretical predictions of Abreu and Brunnermeier (2002), who argue that, in the presence of synchronization risk, rational arbitrageurs will not correct mispricing right away and may even trade in the same direction of the mispricing. Supporting this prediction, Brunnemeier and Nagel (2004) present evidence that hedge funds were riding the technology bubble during 1999–2000.

Alternatively, the negative anomaly loadings on the returns may be due to the agency problem in professional money management. Lakonishok et al. (1994), for example, argue that the principal-agent conflict between the money managers and investors and the short-term evaluation period may induce money managers to exhibit preferences for stock characteristics (e.g., growth stocks) that have done well in the past but have poor future performance. In particular, fund managers might prefer glamour stocks because they appear to be prudent investments and therefore easy to justify to fund investors.

The agency explanation makes two testable predictions. First, the negative anomaly loadings should be concentrated in the short leg of the anomalies. This is

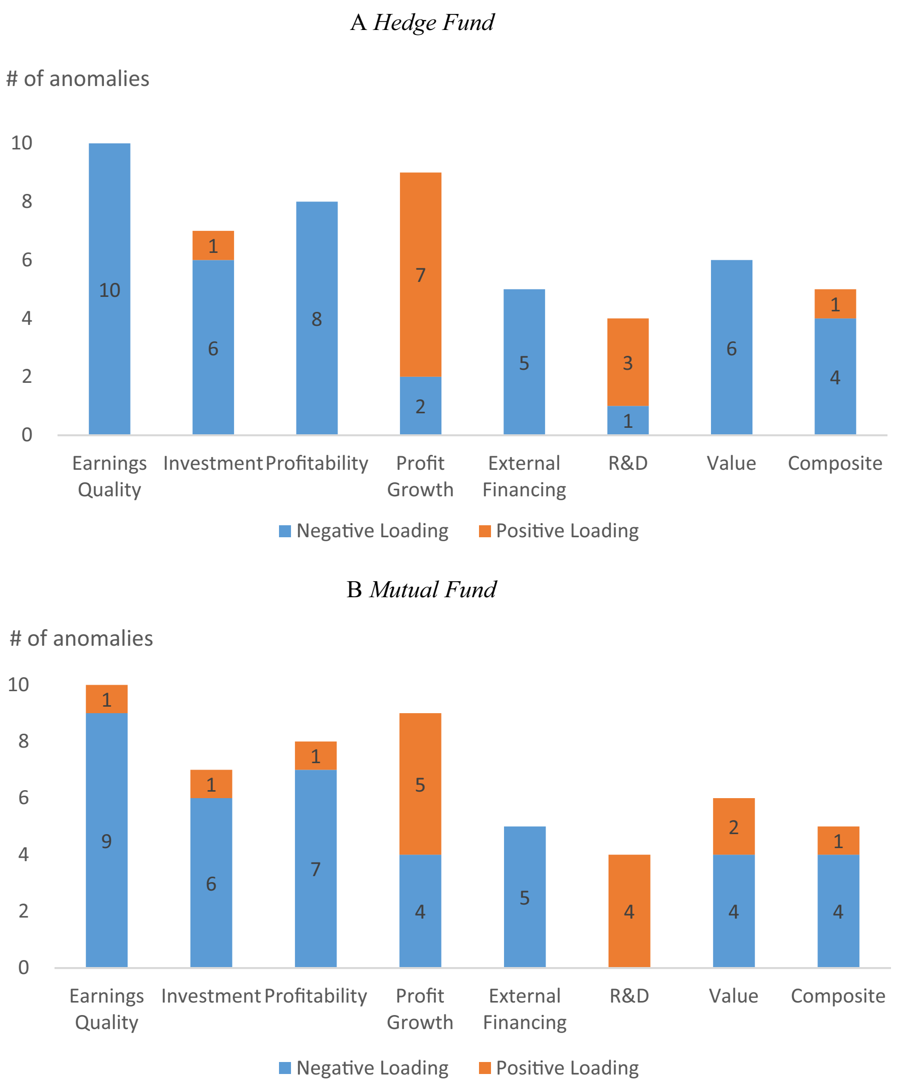


Fig. 1 Number of Positive and Negative Loadings by Anomaly Categories**.** This figure shows the frequencies of negative loadings versus positive loadings for each anomaly category. The detailed list and definitions of the 54 anomalies are contained in the Appendix. Our sample period is from 1994 to 2020. We group our sample anomalies by using the agglomerative clustering approach (Jensen et al. 2022; Murtagh and Legendre 2014). We first compute hedge fund or mutual fund equal-weighted aggregate returns and then regress the aggregate returns on the time series of anomaly returns to obtain loadings

because agency considerations primarily incentivize fund managers to hold overpriced, glamour stocks. The results presented in Table 3 are consistent with this prediction. Specifically, we find that fund returns vary positively with the returns of both long and short legs, suggesting that the observed negative anomaly loadings are primarily driven by the short leg of the anomalies.

The second prediction of the agency explanation is that the negative anomaly loadings should be more pronounced among contrarian-like anomalies than among momentum-like anomalies. This is because contrarian-like anomalies are driven by market overreaction, which causes glamour stocks to be overpriced. In contrast, momentum-like anomalies are driven by market underreaction, which means overpricing only occurs when bad news is not fully incorporated into prices (i.e., among past underperforming stocks).

To test this prediction, we classify the 54 accounting anomalies as either momentum-like and contrarian-like anomalies. For each anomaly, we first compute the returns of the long-short portfolios during the formation-period (i.e., the one-year period prior to the anomaly formation date). We then compare the formation period returns with the holding period returns. If the formation period returns and the holding period returns are in the same direction, we classify the anomaly as a momentum-like anomaly. For example, firms with higher earnings scaled by total assets tend to have higher returns during both the formation period and the holding period (Balakrishnan et al. 2010). Therefore, the profit/loss anomaly of Balakrishnan et al. (2010) is a momentum-like anomaly. Conversely, if the holding period returns and formation period returns are in the opposite direction, we classify it as a contrarian-like anomaly. For example, value stocks tend to outperform growth stocks during the holding period, but underperform growth stocks during the formation period. Therefore, the book-to-market anomaly is a contrarian-like anomaly. Another way to think about this is that momentum-like anomalies are related to market under-reaction, while contrarian-like anomalies are related to market over-reaction. Overall, 28 of our sample anomalies are classified as contrarian-like anomalies, while the remaining 26 are classified as momentum-like anomalies.

We create a dummy variable, *Contrarian*, which takes the value of one if the anomaly is contrarian-like and zero otherwise. We then estimate a cross-sectional regression of the anomaly loadings reported in Table 3 on the *Contrarian* dummy. We report the regression results in Table 4. The dependent variable is either the anomaly loading coefficient (Panel A) or the *t*-statistic of the anomaly loading coefficient (Panel B). We find a significant negative relation between anomaly loadings and the *Contrarian* dummy, suggesting that negative anomaly loadings documented earlier are significantly more pronounced for contrarian-like anomalies.[8] The intercepts of these regressions are statistically insignificant, suggesting that on average

[8] This finding is consistent with a simple count of the positive and negative loadings among momentum- and contrarian-like anomalies in Table 3. For hedge funds, 14 of the 26 momentum-like anomalies have negative loadings, while all 28 contrarian-like anomalies have negative loadings. For mutual funds, 15 of 26 momentum-like anomalies have negative loadings, while 26 of the 28 contrarian-like anomalies have negative loadings. For details, please refer to Figure IA.1 in the Internet Appendix.

Table 4 Contrarian-like anomalies and anomaly loadings

Panel A: Loadings		
	Hedge Funds	Mutual Funds
Intercept	-0.00	-0.01
	(-0.08)	(-0.67)
Contrarian	-0.04	-0.03
	(-5.02)	(-2.74)
R^2	32.65%	12.62%
Number of Observations	54	54

Panel B: Loading t-statistics		
	Hedge Funds	Mutual Funds
Intercept	0.03	-0.45
	(0.08)	(-0.60)
Contrarian	-3.39	-2.61
	(-5.67)	(-2.51)
R^2	38.20%	10.80%
Number of Observations	54	54

This table examines the relation between fund aggregate anomaly loadings and anomaly types. Hedge fund data are obtained from the Lipper TASS database, and mutual fund data are obtained from CRSP mutual fund database. The list and definitions of the 54 accounting anomalies are contained in the Appendix. We obtain monthly stock data from the CRSP, accounting data from Compustat, and analyst forecast data from I/B/E/S. Our sample consists of NYSE, AMEX, and NASDAQ common stocks (with a CRSP share code of 10 or 11). We exclude financial stocks and stocks with a price lower than \$5. We sort all sample stocks into deciles based on each anomaly variable and construct value-weighted portfolios. We first compute hedge fund or mutual fund equal-weighted aggregate returns and then regress the aggregate fund return on the time series of anomaly returns. Our sample period is from 1994 to 2020. We classify the 54 accounting anomalies into two types, momentum and contrarian. An anomaly is contrarian (momentum) type if the holding period returns and formation period returns are in the opposite (same) direction. We estimate a cross-sectional regression of the aggregate anomaly loading or its *t*-statistics on the *Contrarian* dummy. Numbers in parentheses are *t*-statistics

the anomaly loadings are indistinguishable from zero for momentum-like anomalies. The R^2 for these regressions ranges from 10 to 38%, which is quite high, considering that these are univariate regressions—the only explanatory variable is the *Contrarian* dummy variable. Overall, we find that the negative loadings on anomaly returns are more prevalent among contrarian-like anomalies,[9] suggesting that fund managers overreact to certain accounting information. Taken together, our findings that the negative anomaly loadings are driven by the short leg of the anomalies and more pronounced among contrarian-like anomalies provide strong support for the agency explanation.

[9] We note that the negative loadings for contrarian-like anomalies could be driven by fund managers engaging in momentum trading, but failing to unwind positions in a timely manner. Specifically, for contrarian-like anomalies, the long-short return during the formation period is negative, so fund managers engaging in momentum-trading will tend buy (sell) short- (long-) leg stocks during the formation period. If they do not unwind these positions in a timely fashion, they will hold positions opposite to the prescriptions of contrarian-like anomalies during the holding period. We thank the referee for suggesting this alternative explanation.

4.3 Anomaly loadings and fund performance

Trading on accounting anomalies incurs significant transactions costs. It is not clear whether hedge funds and mutual funds that trade on accounting anomalies can deliver superior performance after trading costs. To investigate this issue, we first estimate anomaly loadings at the individual fund level by using the same approach as that for aggregate fund returns.[10]

Table 5 presents the summary statistics of the cross-fund distribution of the *t*-statistics of the anomaly loading coefficients (i.e., the median, the 10th percentile, and the 90th percentile). Panel A presents the results for hedge funds, and Panel B presents the results for mutual funds. We find that fund-level anomaly loadings are disproportionately negative. For example, the median *t*-statistic on the anomaly loading is negative in 38 of the 54 anomalies for hedge funds and is negative in 33 of the 54 anomalies for mutual funds.

Next, for each fund, we compute the average anomaly loading across all 54 accounting anomalies. We then link fund performance to the fund's average anomaly loading. Panel A of Table 6 reports the results for hedge funds. We estimate two regression models. Model 1 is a univariate regression of each fund's seven-factor alpha on its average anomaly loading. We find a significant and positive relation between the average anomaly loading and fund performance. The result is highly statistically significant with a *t*-statistic of 6.26. This result suggests that funds with higher average anomaly loadings tend to perform better. Model 2 expands Model 1 and controls for various fund characteristics. The relation between the average anomaly loading and fund performance remains positive and highly significant. Panel B presents the results for mutual funds. The results are qualitatively similar to and statistically stronger than those for hedge funds. We find that mutual fund performance is positively related to the average anomaly loading. The results are highly statistically significant. The R^2 of these regressions are also much higher than those for hedge funds. Overall, our results suggest that, even though most funds do not trade on accounting anomalies, those funds that are sophisticated enough to do so exhibit superior fund performance.

4.4 Fund stockholdings

An innovation of our paper is to use fund returns to evaluate the extent to which fund managers trade on accounting anomalies. In this section, we supplement our fund return analysis by examining the stockholdings of hedge funds and mutual funds.

4.4.1 Aggregate holdings

To evaluate whether fund managers bet on accounting anomalies, we compute average anomaly decile ranks of fund stockholdings. As explained in Sect. 3.1, we sort

[10] We require that funds have at least 24 months of returns. Our final sample for fund-level analyses include 4,645 hedge funds and 2,866 mutual funds.

Table 5 Distribution of fund-level anomaly loading *t*-statistics

Panel A: Earnings Quality

Anomaly	Hedge Funds			Mutual Funds		
	P50	P10	P90	P50	P10	P90
TAcc	-0.67	-2.72	1.06	-0.54	-4.05	2.81
PTAcc	-0.54	-2.32	1.29	-0.44	-3.54	2.71
OAcc	-0.05	-1.51	1.36	-0.67	-2.84	1.55
POAcc	0.15	-1.30	1.53	-0.23	-2.20	1.76
AG	-0.71	-2.97	1.30	0.01	-5.97	6.04
BrandCap	-0.24	-1.77	1.19	-0.18	-2.24	1.86
dSales	-0.79	-3.07	1.14	-0.32	-5.93	4.86
dBE	-0.64	-2.52	1.23	-0.13	-4.99	4.62
dOA	-0.75	-2.93	1.20	-0.66	-4.83	4.41
dNCOA	-0.12	-1.93	1.61	0.78	-2.38	4.67

Panel B: Investment

Anomaly	Hedge Funds			Mutual Funds		
	P50	P10	P90	P50	P10	P90
CI	-0.36	-2.10	1.34	-0.39	-3.20	2.65
I/A	-0.93	-3.17	0.99	-0.57	-4.21	3.10
dInv	-0.70	-2.57	1.11	-0.19	-4.15	3.97
dInv_adj	-0.42	-2.05	1.21	-0.42	-3.28	3.28
IG	-0.74	-2.75	1.13	-0.95	-3.85	1.91
dInvent	-0.82	-3.30	1.22	-0.34	-3.27	1.95
NOA	-0.46	-2.31	1.38	-0.46	-3.16	2.34

Panel C: Profitability

Anomaly	Hedge Funds			Mutual Funds		
	P50	P10	P90	P50	P10	P90
ROA	-0.35	-2.08	1.31	-1.06	-6.02	4.28
ROE	-0.40	-2.24	1.26	-1.18	-6.33	5.10
RNOA	-0.04	-1.77	1.51	-1.40	-6.83	4.18
GP/A	-0.38	-2.17	1.36	-0.41	-4.18	5.07
Cturn	-0.23	-1.75	1.20	-0.05	-2.62	2.43
OrgCap	-1.01	-3.87	0.98	-1.08	-4.18	2.35
OperLev	-0.53	-2.30	1.13	0.23	-2.89	3.96
PM	-0.03	-1.97	1.60	-1.33	-7.67	5.25

Table 5 (continued)

Panel D: Profit Growth						
Anomaly	Hedge Funds			Mutual Funds		
	P50	P10	P90	P50	P10	P90
SUE	0.23	-1.50	1.83	0.03	-2.72	3.17
RS	-0.21	-1.94	1.76	-0.75	-5.09	3.67
TaxExp	0.41	-1.31	2.21	-0.21	-3.77	3.76
EAR	0.60	-1.19	2.72	0.08	-3.44	4.63
SA_SGA	0.73	-0.85	2.43	0.32	-1.75	2.35
SA_IV	-0.22	-1.65	1.30	-0.52	-2.71	1.54
dNWC	0.00	-1.54	1.73	-0.40	-4.42	2.51
dAturn	0.30	-1.13	1.56	0.55	-1.28	2.23
dPM	0.32	-1.23	1.87	0.41	-1.84	2.84

Panel E: External Financing						
Anomaly	Hedge Funds			Mutual Funds		
	P50	P10	P90	P50	P10	P90
Xfin	-0.91	-3.69	1.23	-1.92	-8.75	5.84
NSI	-0.92	-2.99	1.05	-1.57	-6.33	4.34
Payout	-0.83	-3.89	1.28	-0.14	-8.16	8.05
Npayout	-1.02	-3.86	1.07	-1.13	-7.26	5.81
TI/BI	0.31	-1.57	1.83	-0.03	-5.13	4.85

Panel F: R&D						
Anomaly	Hedge Funds			Mutual Funds		
	P50	P10	P90	P50	P10	P90
R&D/A	0.16	-1.68	2.52	0.68	-6.17	9.13
R&D/M	-0.02	-1.64	1.70	1.17	-1.59	3.88
Aturn	-0.05	-1.73	1.78	-0.18	-5.26	5.42
AccQ	0.70	-1.24	2.78	1.38	-4.31	5.68

Table 5 (continued)

Panel G: Value						
Anomaly	Hedge Funds			Mutual Funds		
	P50	P10	P90	P50	P10	P90
E/P	0.23	-1.96	2.05	0.64	-6.61	7.61
CF/P	0.02	-2.32	1.84	0.80	-7.06	8.21
B/M	-0.52	-3.13	1.68	0.74	-6.75	8.30
A/M	-0.50	-3.18	1.72	0.55	-7.62	8.98
S/P	-0.45	-2.93	1.68	0.89	-6.87	9.08
AD/M	-0.49	-3.02	1.58	0.90	-5.84	7.89

Panel H: Composite						
Anomaly	Hedge Funds			Mutual Funds		
	P50	P10	P90	P50	P10	P90
F-score	0.40	-1.37	2.09	0.29	-3.53	4.70
G-score	-0.74	-2.45	0.91	-2.10	-6.09	3.02
PS	-0.15	-1.97	1.58	0.01	-6.50	5.91
LM	0.18	-1.61	2.00	1.36	-4.23	6.87
V/P	0.70	-1.26	3.01	0.18	-2.72	3.35

This table reports the distribution of fund-level anomaly loading *t*-statistics. Hedge fund data are from the Lipper TASS database. We remove the first 12 months' observations for each fund. We also remove all observations before a fund reaches \$10 million in total net assets. We only retain funds that invest in equity markets and report net returns on a monthly basis in U.S. dollars. Mutual fund data are from the CRSP Mutual Fund Database. We combine different share classes of the same fund into a single fund. We restrict our analysis to U.S. domestic actively managed equity mutual funds. We also exclude funds that have less than 80% of their holdings in common stocks. We include a fund only after its TNA has surpassed \$15 million. We also exclude observations prior to the first offer date of the fund. For fund-level analysis, we further require that funds have at least 24 months of returns. Our final sample includes 4,645 hedge funds and 2,866 mutual funds. For each fund, we regress fund returns on the time series of anomaly returns to obtain anomaly loadings. We group our sample anomalies by using the agglomerative clustering approach (Jensen et al. 2022; Murtagh and Legendre 2014) and organize our panels by anomaly category. P10 is the 10^{th} percentile. P50 is the 50^{th} percentile, i.e., the median. P90 is the 90^{th} percentile all sample stocks into deciles based on each accounting anomaly variable, where decile 10 contains stocks that are expected to outperform (i.e., long-leg stocks) and decile 1 contains stocks that are expected to underperform (i.e., short-leg stocks). If fund managers exploit accounting anomalies, we would expect the average anomaly decile ranks of their holdings to be relatively high, compared to their benchmarks.

Similar to our fund return analysis, we first perform the analysis at the aggregate level. Specifically, we combine individual funds' quarter-end stockholdings to construct an aggregate portfolio for hedge funds or mutual funds. Next, we calculate the dollar holding-weighted average anomaly decile rank for the aggregate portfolio. We then compare the anomaly decile rank of the aggregate portfolio to that of the benchmark portfolio. We consider three benchmark portfolios for the aggregate hedge fund or mutual fund portfolios: the market portfolio, S&P500 index portfolio, and the Russell 1000 index portfolio. The difference in the anomaly decile rank between the aggregate fund portfolio and the benchmark portfolio, i.e., the excess anomaly rank, is our primary variable of interest. It measures the funds' tendency to overweight or underweight stocks with a particular anomaly characteristic relative to the benchmark. Take the accruals anomaly as an example. If the average decile rank for the aggregate hedge fund portfolio is six and the average decile rank of the S&P 500 portfolio is five, then the excess anomaly rank would be one, and we would conclude that hedge funds are betting on the accruals anomaly. Conversely, if the excess anomaly rank is negative, then we would conclude that fund managers are betting in the opposite direction of the accruals anomaly.

We perform the analysis anomaly by anomaly and separately for hedge funds and mutual funds. For each anomaly, we compute the excess anomaly rank each quarter and then report the time-series average of the excess anomaly rank along with its Newey-West adjusted t-statistics. Table 7 presents the results. As in previous tables, we organize the results by anomaly categories.

The results in Table 7 indicate that excess anomaly ranks tend to be negative for both hedge funds and mutual funds. For example, when we use the S&P 500 index portfolio as the benchmark, the excess anomaly rank is negative among 35 (36) of the 54 sample anomalies for hedge funds (mutual funds), the majority of which are statistically significant. The results are qualitatively identical when we use the other two benchmark portfolios. These findings are consistent with our earlier findings based on fund returns and suggest that fund managers tend to bet in the wrong direction of accounting anomalies. Also similar to our results from fund returns, we find that negative excess anomaly ranks are most prevalent among the anomalies in the earnings quality, investment, profitability, external financing, and composite categories, and that the excess anomaly ranks tend to be positive for anomalies in the *R&D* and *Profitability Growth* categories.

4.4.2 Fund-level holdings

We also calculate the average anomaly decile rank of stockholdings at the individual fund level. To compute the excess anomaly rank at the fund level, we compare each

Table 6 Anomaly loadings and fund performance

Panel A: Hedge Fund		
	(1)	(2)
Intercept	0.18	-1.78
	(12.00)	(-5.91)
Average Anomaly Loading	0.09	0.08
	(6.26)	(5.12)
Log (AUM)		0.06
		(3.55)
Log (Age)		0.02
		(0.87)
Management Fee		0.03
		(0.85)
Incentive Fee		0.01
		(3.98)
High Watermark		0.07
		(2.10)
Personal Capital		0.00
		(0.02)
Log (minimum investment)		0.04
		(3.00)
Log (redemption notice period)		0.03
		(2.31)
Log (lock-up period)		0.02
		(2.35)
No. obs	4,645	4,140
Adj R^2	0.4%	3.7%
Panel B: Mutual Fund		
	(1)	(2)
Intercept	-0.13	-0.66
	(-22.15)	(-10.87)
Average Anomaly Loading	0.02	0.02
	(7.08)	(5.13)
Log (AUM)		0.03
		(6.47)
Log (Age)		0.11
		(7.90)
Expense ratio		-0.03
		(-1.48)
Turnover ratio		-0.02
		(-1.32)
Total Load		-2.57

Table 6 (continued)

		(-4.98)
No. obs	2,866	2,643
Adj R^2	1.3%	15.5%

This table reports the relation between each fund's average anomaly loadings and fund performance. Hedge fund data are obtained from the Lipper TASS database, and mutual fund data are obtained from CRSP mutual fund database. For fund-level analysis, we further require that funds have at least 24 months of returns. Our final sample includes 4,645 hedge funds and 2,866 mutual funds. The list and definitions of the 54 accounting anomalies are contained in the Appendix. Our sample consists of NYSE, AMEX, and NASDAQ common stocks (with a CRSP share code of 10 or 11). We regress hedge fund's full sample seven-factor alpha on the fund's anomaly loading *t*-statistic averaged across 54 anomalies. We regress mutual fund's full sample one-factor alpha on the fund's anomaly loading *t*-statistic averaged across 54 anomalies. Panel A reports the regression results for hedge funds, and Panel B reports results for mutual funds. Numbers in parentheses are *t*-statistics, which are computed based on White heteroscedasticity consistent standard errors. The sample period is 1994–2020. Total load, expense ratio, and turnover ratio are in percent. Returns and alphas are expressed in percent

fund's anomaly decile rank to that of its benchmark portfolio. For mutual funds, we use the fund's self-declared benchmark obtained from Martijn Cremers.[11] By far the most commonly used benchmark by mutual funds is the S&P 500 index. The other popular benchmarks include Russell 1000, Russell 2000, Russell 3000, and their value/growth and small cap/large cap variants. For hedge funds, we use the S&P 500 index as the benchmark.[12]

We report the median (P50), the 10th percentile (P10), and the 90th percentile (P90) of the *t*-statistics of excess anomaly ranks across all hedge funds or mutual funds in Table 8. As in previous tables, we organize our results by anomaly categories. We find that, for most anomalies, P50 is less than 2 in absolute value, indicating that the median excess anomaly ranks are generally not statistically significant. Among those that are statistically significant, their signs are broadly consistent with what we find in Table 7, i.e., the median excess anomaly rank tends to be negative in the earnings quality, investment, profitability, external financing, and composite categories and positive in the *R&D* and *Profitability Growth* categories.

To present a more complete picture of the cross-fund distribution of excess anomaly ranks, we plot the histogram of the *t*-statistic of excess anomaly ranks in Fig. 2 (Panel A for hedge funds and Panel B for mutual funds). To conserve space, rather than presenting 54 anomaly-level plots, we pool all anomalies in each anomaly category together and plot by anomaly categories. In each plot, in addition to the histogram, we also follow Palhares and Richardson (2020) and plot a corresponding normal distribution for comparison. The normal distribution has a mean equal to zero and the same standard deviation as the actual distribution. By comparing the actual distribution with the normal distribution, we can assess (1) whether the excess anomaly rank is on average positive or negative, (2) whether the excess anomaly rank is skewed to the left or right, and (3) whether the excess anomaly rank has fatter or thinner tails relative to the normal distribution.

[11] The website is https://activeshare.nd.edu/. When the self-declared benchmark is missing for a fund, we use the S&P 500 index as its benchmark.

[12] Our results are similar if we use other popular indexes as the benchmark portfolio for hedge funds.

Table 7 Excess anomaly decile rank of aggregate stock holdings of hedge funds and mutual funds

Panel A: Earnings Quality

Anomaly	Hedge Funds			Mutual Funds		
	Market	S&P500	Russell1000	Market	S&P500	Russell1000
TAcc	-0.12 ***	-0.28 ****	-0.18 ****	-0.38 ***	-0.55 ***	-0.44 ***
PTAcc	-0.13 ***	-0.32 ****	-0.20 ****	-0.34 ***	-0.53 ***	-0.42 ***
OAcc	-0.05 ***	-0.12 ***	-0.09 ***	-0.14 ***	-0.21 ***	-0.18 ***
POAcc	-0.02	-0.03	-0.04	-0.14 ***	-0.15 **	-0.15 ***
AG	-0.13 ***	-0.28 ***	-0.17 ***	-0.49 ***	-0.63 ***	-0.52 ***
BrandCap	-0.06 **	-0.17 ****	-0.08 ***	-0.34 ***	-0.44 ***	-0.36 ***
dSales	-0.18 ****	-0.37 ****	-0.23 ****	-0.60 ***	-0.79 ***	-0.65 ***
dBE	-0.14 ***	-0.28 ****	-0.18 ****	-0.47 ***	-0.61 ***	-0.51 ***
dOA	-0.05 **	-0.16 ***	-0.07 **	-0.28 ***	-0.39 ***	-0.30 ***
dNCOA	0.12 ****	0.34 ****	0.27 ****	0.09 **	0.31 ***	0.25 ***

Panel B: Investment

Anomaly	Hedge Funds			Mutual Funds		
	Market	S&P500	Russell1000	Market	S&P500	Russell1000
CI	0.00	0.04	0.03	0.02	0.06	0.04
I/A	-0.06 **	-0.19 ***	-0.08 **	-0.27 ***	-0.40 ***	-0.29 ***
dInv	-0.07 ***	-0.14 ***	-0.08 ***	-0.20 ***	-0.27 ***	-0.22 ***
dInv_adj	-0.08 ***	-0.15 ***	-0.08 **	-0.25 ***	-0.32 ***	-0.26 ***
IG	-0.10 ***	-0.21 ***	-0.13 ***	-0.34 ***	-0.45 ***	-0.37 ***
dInvent	-0.10 ***	-0.21 ****	-0.14 ***	-0.34 ***	-0.45 ***	-0.38 ***
NOA	-0.05 ***	-0.25 ****	-0.12 ****	-0.18 ***	-0.37 ***	-0.24 ***

Panel C: Profitability

Anomaly	Hedge Funds			Mutual Funds		
	Market	S&P500	Russell1000	Market	S&P500	Russell1000
ROA	-0.04 ***	-0.29 ****	-0.17 ****	-0.02	-0.27 ***	-0.14 ***
ROE	-0.08 ****	-0.40 ****	-0.25 ****	-0.16 ***	-0.48 ***	-0.32 ***
RNOA	-0.01	-0.25 ****	-0.14 ***	0.07	-0.17 **	-0.05
GP/A	0.00	-0.12 ***	-0.04 *	0.19 ***	0.07	0.15 ***
Cturn	0.08 ***	0.17 ***	0.13 ***	0.30 ***	0.38 ***	0.35 ***
OrgCap	-0.06 ***	-0.19 ***	-0.05 *	-0.10 *	-0.23 ***	-0.09
OperLev	0.06 ***	0.15 ****	0.13 ****	0.19 ***	0.28 ***	0.26 ***
PM	-0.10 ****	-0.43 ****	-0.29 ****	-0.25 ***	-0.57 ***	-0.43 ***

Panel D: Profit Growth

Anomaly	Hedge Funds			Mutual Funds		
	Market	S&P500	Russell1000	Market	S&P500	Russell1000
SUE	0.04 ***	-0.02	-0.00	0.16 ***	0.10 **	0.12 ***
RS	0.05 **	0.01	-0.01	0.35 ***	0.31 ***	0.29 ***
TaxExp	0.10 ****	0.13 ****	0.10 ****	0.25 ***	0.28 ***	0.24 ***
EAR	0.07 ****	0.10 ****	0.08 ****	0.14 ***	0.17 ***	0.15 ***
SA_SGA	0.06 ***	0.09 ****	0.07 ***	0.09 **	0.13 ***	0.10 ***
SA_IV	0.02	0.04	0.03	0.05 **	0.07 **	0.06 *
dNWC	-0.03	-0.08 *	-0.04	-0.09 **	-0.14 ***	-0.10 **
dAturn	0.06 ***	0.07 ***	0.06 ***	0.06	0.07 *	0.06
dPM	0.09 ****	0.13 ****	0.10 ****	0.15 ***	0.19 ***	0.16 ***

Table 7 (continued)

Panel E: External Financing

Anomaly	Hedge Funds			Mutual Funds		
	Market	S&P500	Russell1000	Market	S&P500	Russell1000
Xfin	-0.21 ****	-0.59 ****	-0.37 ****	-0.49 ***	-0.87 ***	-0.65 ***
NSI	-0.21 ****	-0.57 ****	-0.37 ****	-0.53 ***	-0.89 ***	-0.69 ***
Payout	-0.29 ****	-0.72 ****	-0.47 ****	-0.78 ***	-1.20 ***	-0.95 ***
Npayout	-0.29 ****	-0.70 ****	-0.46 ****	-0.71 ***	-1.11 ***	-0.88 ***
TI/BI	0.02 **	0.03 *	0.02	0.03	0.04	0.03

Panel F: R&D

Anomaly	Hedge Funds			Mutual Funds		
	Market	S&P500	Russell1000	Market	S&P500	Russell1000
R&D/A	0.22 ****	0.29 ****	0.28 ****	0.46 ***	0.53 ***	0.52 ***
R&D/M	0.17 ***	0.25 ****	0.25 ****	0.19 ***	0.27 ***	0.27 ***
Aturn	0.09 **	0.11 **	0.11 ***	0.31 ***	0.33 ***	0.34 ***
AccQ	0.25 ****	0.46 ****	0.36 ****	0.52 ***	0.73 ***	0.63 ***

Panel G: Value

Anomaly	Hedge Funds			Mutual Funds		
	Market	S&P500	Russell1000	Market	S&P500	Russell1000
E/P	-0.11 ***	-1.06 ****	-0.95 ****	-0.43 ***	-1.39 ***	-1.28 ***
CF/P	-0.10 ***	-0.87 ****	-0.79 ****	-0.45 ***	-1.24 ***	-1.16 ***
B/M	0.01	0.18 ***	0.13 ***	-0.18 ***	-0.02	-0.06
A/M	-0.02	0.07	0.04	-0.34 ***	-0.25 ***	-0.28 ***
S/P	0.01	0.10 ***	0.09 ***	-0.17 ***	-0.08 ***	-0.09 ***
AD/M	-0.07 ***	-0.12 ***	-0.05 *	-0.26 ***	-0.31 ***	-0.24 ***

Panel H: Composite

Anomaly	Hedge Funds			Mutual Funds		
	Market	S&P500	Russell1000	Market	S&P500	Russell1000
F-score	0.04 **	-0.04	-0.01	0.08 **	-0.01	0.03
G-score	-0.13 ****	-0.39 ****	-0.25 ****	-0.14 ***	-0.40 ***	-0.27 ***
PS	-0.01	-0.00	-0.00	-0.04 ***	-0.03 ***	-0.03 ***
LM	0.00	-0.01	-0.00	-0.01	-0.02	-0.01
V/P	0.08 **	-0.02	0.04	-0.13 *	-0.23 **	-0.17 *

This table reports the excess anomaly decile rank of aggregate stock holdings of hedge funds or mutual funds. We group our sample anomalies by using the agglomerative clustering approach (Jensen et al. 2022; Murtagh and Legendre 2014) and organize our panels by anomaly category. We obtain mutual fund stock holdings from the Thomson Reuters Mutual Fund Holdings Database. We obtain hedge funds' quarterly stock holdings by merging TASS with the Thomson Reuters 13F database. We identify hedge fund companies in the 13F database by manually matching the institutional investors' names from 13F with the asset management companies' names from Lipper TASS. For stock holdings analyses, the number of mutual funds is 2,800, and the number of hedge fund companies is 650. The sample period is from 1994 to 2020. We combine individual funds' stock holdings to obtain the aggregate holdings for hedge funds or mutual funds each quarter. We sort stocks into deciles based on each accounting anomaly variable. For each anomaly, we calculate the dollar-weighted average anomaly decile rank for the aggregate portfolio. We compare this average decile rank with that of the benchmark portfolio to obtain the excess anomaly rank. We consider three benchmark portfolios: the market portfolio, the S&P 500 index portfolio, and the Russell 1000 index portfolio. For each anomaly, we compute the time-series average excess anomaly rank and its Newey-West adjusted t-statistics with 7 lags. We use *, **, *** and **** for $|t\text{-stats}|\geq 1.65$, $|t\text{-stats}|\geq 1.96$, $|t\text{-stats}|\geq 2.58$ and $|t\text{-stats}|\geq 5$, respectively

Panel A of Fig. 2 reveals that the average excess anomaly ranks for hedge funds are significantly negative for the earnings quality, investment, profitability, external financing, and composite categories and significantly positive for the *R&D* category. For the *Value* and *Profitability Growth* categories, the distribution of the excess anomaly ranks appears to center around zero. The results for mutual funds presented in Panel B are qualitatively similar. Specifically, the average excess anomaly rank is significantly negative for the earnings quality, investment, and external financing categories, slightly negative for the profitability, value, and composite categories, slightly positive for the profitability growth category, and significantly positive for the *R&D* category. Overall, these results are broadly consistent with what we find for the aggregate holdings as well as fund returns.

In Fig. 3, we pool the excess anomaly ranks across all anomalies and then plot their distribution across funds. We also plot the distribution of excess anomaly ranks across all contrarian anomalies and all momentum anomalies, respectively. As before, we examine hedge funds and mutual funds separately, so there are a total of six charts in Fig. 3. Looking at the charts for all anomalies, we find that, for both hedge funds and mutual funds, the distribution of excess anomaly ranks is significantly skewed to left, suggesting that the excess anomaly ranks for hedge funds are predominantly negative. The negative skewness is more pronounced for contrarian-like anomalies. In contrast, the distribution for momentum-like anomalies is more symmetric and only slightly negatively skewed. The results for mutual funds are qualitatively similar. We continue to find that the distribution of excess anomaly ranks is significantly skewed to left for all anomalies. This finding is primarily driven by contrarian-like anomalies. In contrast, the distribution for momentum-like anomalies is more symmetric.

4.4.3 Time-series of excess anomaly ranks

In this section, we explore the time-series variation of excess anomaly ranks. Specifically, in Fig. 4, we plot the average excess anomaly ranks across all hedge funds or mutual funds over time. As in Figs. 2 and 3, we plot by anomaly categories. Three findings stand out. First, these charts generally confirm the results in Figs. 2 and 3 that the average excess anomaly rank tends to be negative in the earnings quality, investment, profitability, external financing, and composite categories and positive in the *R&D* and *Profitability Growth* categories. Second, there is large time-series variation in the excess anomaly ranks. For example, for the *Earnings Quality* category, even though the excess anomaly rank is negative during most of 1994–2020, it turns slightly positive in the early 2000s, mid-2000s, and early 2010s. Third, there is a modest level of co-movement between hedge funds and mutual funds in the time-series variation of excess anomaly ranks.

To show how the average excess anomaly ranks vary over time overall, we plot in Fig. 5 the time-series of the average excess anomaly rank aggregated across all anomalies. We also plot the average excess anomaly ranks aggregated across all contrarian-like anomalies and momentum-like anomalies, respectively, to check whether excess anomaly ranks differ significantly across contrarian- and momentum-like anomalies and whether this difference varies over

Table 8 Distribution of the excess anomaly rank of fund-level stock holdings

Panel A: Earnings Quality

Anomaly	Hedge Funds			Mutual Funds		
	P50	P10	P90	P50	P10	P90
TAcc	-2.16	-6.32	1.04	-2.38	-7.65	2.25
PTAcc	-2.93	-7.62	0.11	-2.61	-8.29	1.69
OAcc	-0.95	-4.55	2.74	-1.54	-5.39	2.45
POAcc	0.96	-3.88	5.47	-0.78	-5.94	5.04
AG	-1.22	-6.49	2.35	-1.66	-7.79	4.66
BrandCap	-0.90	-4.83	2.32	-0.92	-5.46	3.35
dSales	-2.12	-8.25	1.96	-1.99	-9.24	4.26
dBE	-1.67	-6.73	1.54	-2.11	-8.28	3.27
dOA	-0.92	-4.93	2.43	-1.30	-6.36	3.50
dNCOA	2.91	-0.70	8.34	1.81	-1.99	8.32

Panel B: Investment

Anomaly	Hedge Funds			Mutual Funds		
	P50	P10	P90	P50	P10	P90
CI	0.82	-1.39	3.16	0.59	-1.86	3.30
I/A	-0.81	-5.29	2.67	-1.27	-5.53	3.40
dInv	-1.14	-4.45	1.34	-1.23	-5.47	2.77
dInv_adj	-0.90	-4.36	1.74	-1.14	-5.40	3.06
IG	-1.28	-5.45	1.59	-1.66	-6.87	2.98
dInvent	-1.28	-5.61	2.05	-1.91	-7.17	2.67
NOA	-2.34	-7.25	2.22	-2.47	-8.41	2.35

Panel C: Profitability

Anomaly	Hedge Funds			Mutual Funds		
	P50	P10	P90	P50	P10	P90
ROA	-5.31	-14.25	1.01	-1.25	-10.46	4.57
ROE	-5.49	-13.41	-0.01	-2.04	-11.35	3.58
RNOA	-4.37	-11.92	1.51	-1.05	-9.74	4.84
GP/A	-2.36	-10.07	2.72	0.07	-6.64	5.75
Cturn	0.66	-4.49	6.34	2.52	-2.12	9.49
OrgCap	-1.92	-8.23	2.31	-0.97	-6.18	4.54
OperLev	1.07	-4.09	7.29	2.23	-2.22	10.84
PM	-5.28	-13.85	-0.05	-2.34	-13.35	2.16

Table 8 (continued)

Panel D: Profit Growth						
Anomaly	Hedge Funds			Mutual Funds		
	P50	P10	P90	P50	P10	P90
SUE	-1.89	-5.51	3.26	0.38	-5.34	5.87
RS	-1.61	-6.38	3.46	0.60	-5.60	6.45
TaxExp	-0.02	-2.68	4.69	1.24	-3.53	6.28
EAR	1.13	-1.49	5.99	1.64	-1.77	6.40
SA_SGA	0.52	-1.58	3.64	0.82	-1.88	4.12
SA_IV	0.60	-1.77	3.23	0.28	-2.12	3.37
dNWC	-0.54	-3.06	1.84	-1.21	-4.35	1.56
dAturn	0.66	-1.35	2.84	0.43	-1.75	3.08
dPM	0.93	-1.73	4.79	1.03	-2.99	5.96
Panel E: External Financing						
Anomaly	Hedge Funds			Mutual Funds		
	P50	P10	P90	P50	P10	P90
Xfin	-5.69	-13.50	-0.90	-2.84	-11.59	1.48
NSI	-5.15	-14.51	-0.51	-2.40	-12.60	2.46
Payout	-6.05	-14.38	-0.86	-2.99	-14.84	3.15
Npayout	-5.90	-15.76	-1.19	-3.18	-15.79	2.58
TI/BI	-0.23	-3.99	3.94	0.92	-2.49	4.94
Panel F: R&D						
Anomaly	Hedge Funds			Mutual Funds		
	P50	P10	P90	P50	P10	P90
R&D/A	1.21	-4.02	8.26	0.53	-5.90	7.91
R&D/M	2.21	-1.99	7.82	0.86	-3.39	6.20
Aturn	0.16	-5.15	6.62	1.59	-3.80	7.92
AccQ	4.69	0.28	12.00	3.10	-1.24	13.38

Table 8 (continued)

Panel G: Value						
Anomaly	Hedge Funds			Mutual Funds		
	P50	P10	P90	P50	P10	P90
E/P	-4.74	-14.17	0.14	-4.71	-16.57	0.84
CF/P	-3.30	-12.67	1.84	-3.83	-15.79	2.85
B/M	2.61	-3.55	9.46	0.97	-6.80	10.06
A/M	2.87	-4.90	11.16	0.33	-7.96	10.30
S/P	1.86	-4.29	10.91	1.08	-7.00	11.43
AD/M	0.05	-5.03	4.64	-0.59	-6.49	5.00

Panel H: Composite						
Anomaly	Hedge Funds			Mutual Funds		
	P50	P10	P90	P50	P10	P90
F-score	-1.06	-4.59	1.68	0.18	-3.05	3.46
G-score	-5.72	-15.03	-0.79	-2.50	-13.17	2.32
PS	-0.06	-3.81	3.02	0.09	-3.91	3.91
LM	-0.05	-2.92	3.12	0.81	-2.28	3.96
V/P	-0.68	-5.97	3.35	0.57	-5.10	6.22

This table reports the distribution of the *t*-statistics of excess anomaly rank across sample funds. We group our sample anomalies by using the agglomerative clustering approach (Jensen et al. 2022; Murtagh and Legendre 2014) and organize our panels by anomaly category. We obtain mutual fund stock holdings from the Thomson Reuters Mutual Fund Holdings Database. We obtain hedge funds' quarterly stock holdings by merging TASS with the Thomson Reuters 13F database. We identify hedge fund companies in the 13F database by manually matching institutional investors' names from 13F with asset management companies' names from Lipper TASS. The number of mutual funds is 2,800, and the number of hedge fund companies is 650. The sample period is 1994–2020. We calculate the fund-level excess anomaly rank, relative to the fund's self-declared benchmark. Mutual funds' benchmarks are obtained from Martijn Cremers' website https://activeshare.nd.edu/. When the benchmark data is missing for a fund, we use the S&P 500 as its benchmark. We obtain the constituents of the S&P 500 index from CRSP. We construct the other indices based on their definitions. For hedge funds, we use the S&P 500 as the benchmark. For each anomaly, we compute the distribution of the Newey-West adjusted *t*-statistics with seven lags across sample funds

A *Hedge Fund*

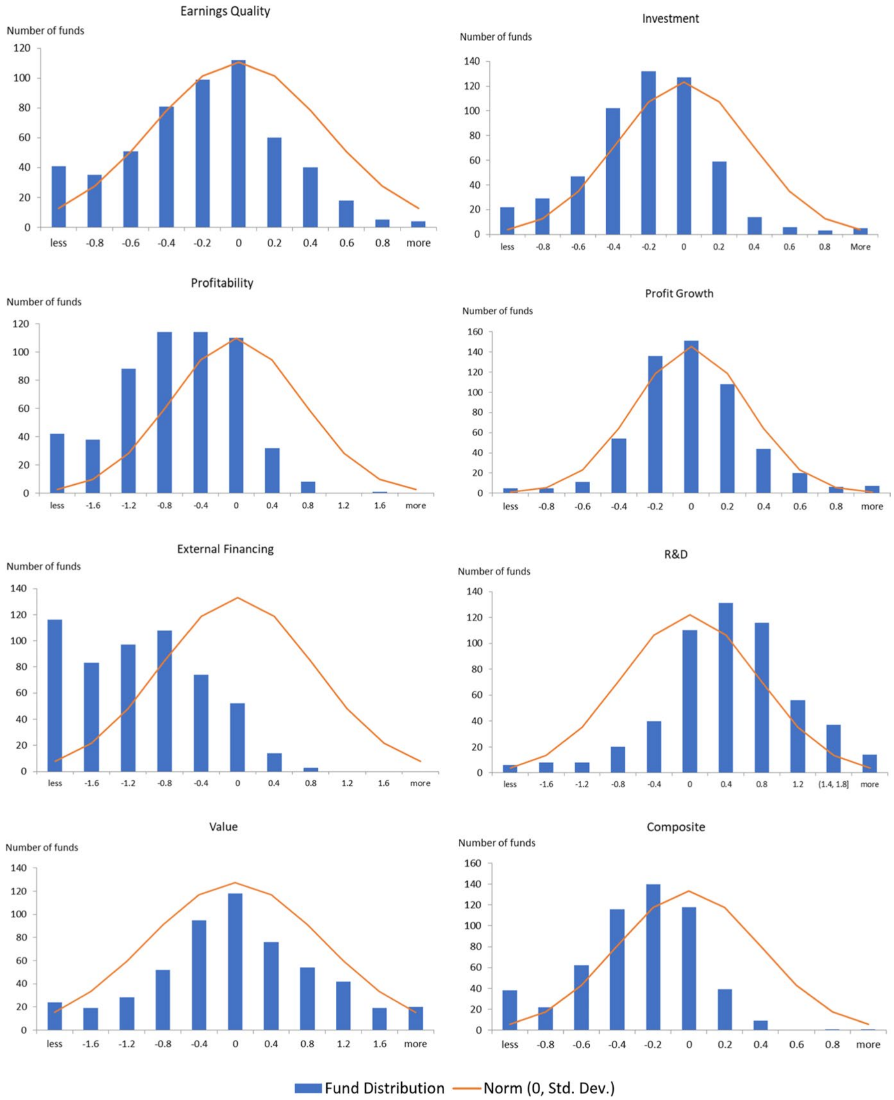


Fig. 2 Distribution of Excess Anomaly Decile Rank of Fund-Level Stock Holdings. This figure shows the distribution of the average excess anomaly decile rank of funds' stock holdings for each category of anomalies. We group our sample anomalies by using the agglomerative clustering approach (Jensen et al. 2022; Murtagh and Legendre 2014). We obtain mutual fund stock holdings from the Thomson Reuters Mutual Fund Holdings Database. We obtain hedge funds' quarterly stock holdings by merging TASS with the Thomson Reuters 13F database. For stock holdings analyses, the number of mutual funds is 2,800 and the number of hedge fund companies is 650. We calculate the fund-level excess anomaly rank relative to the fund's benchmark. Mutual funds' self-declared benchmarks are obtained from Martijn Cremers' website https://activeshare.nd.edu/. When the benchmark data is missing for a fund, we use S&P500 as its benchmark. We obtain the constituents of S&P 500 index from CRSP. We construct the other indices based on their definitions. For hedge funds, we use S&P500 as the benchmark. For each fund, we calculate the average excess decile rank across anomalies in the same category. The orange line in each graph shows a normal distribution with mean of zero and standard deviation equal to that of the actual distribution

B *Mutual Fund*

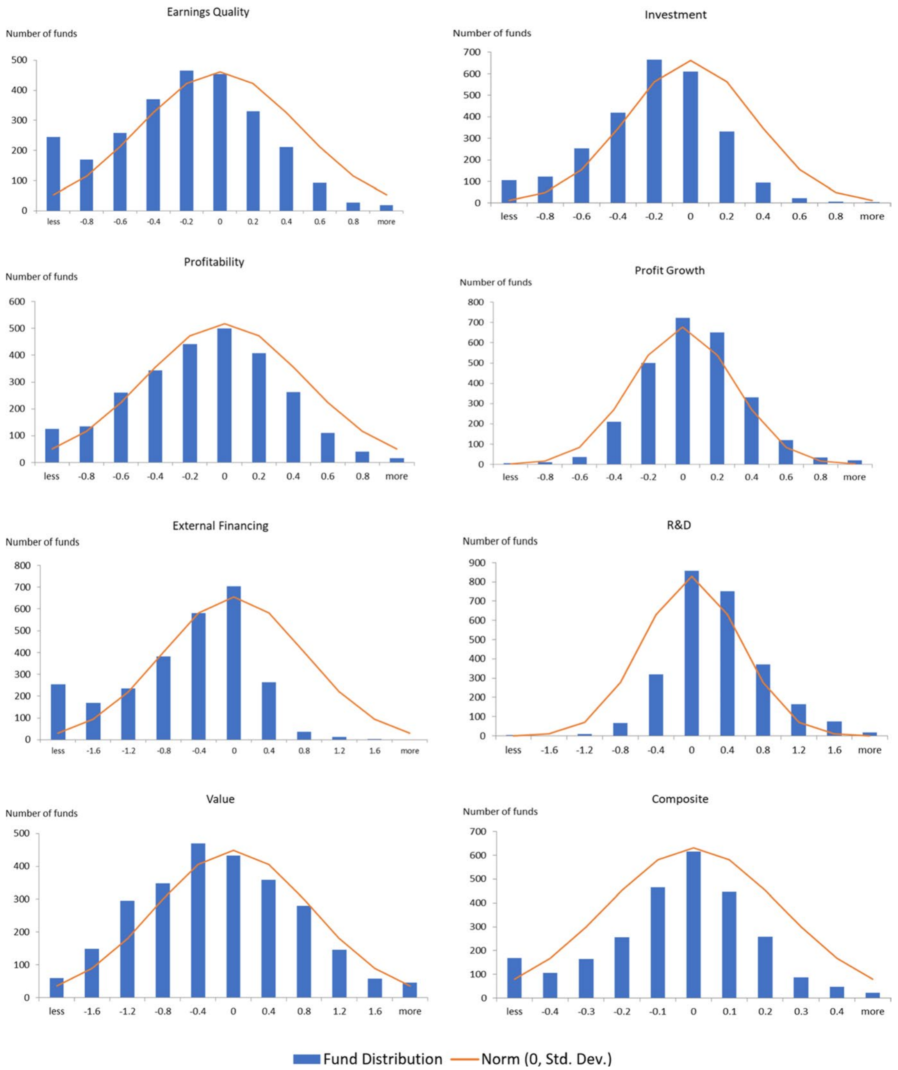


Fig. 2 (continued)

time. Panel A of Fig. 5 contains the chart for hedge funds, while Panel B contains the chart for mutual funds. We report several findings. First, for both hedge funds and mutual funds, the average excess anomaly ranks are persistently negative during our sample period. Second, these negative excess anomaly ranks are primarily driven by contrarian-like anomalies. In fact, for the momentum-like anomalies, the excess anomaly ranks are frequently positive, especially for mutual funds. Third, the difference between contrarian- and momentum-like

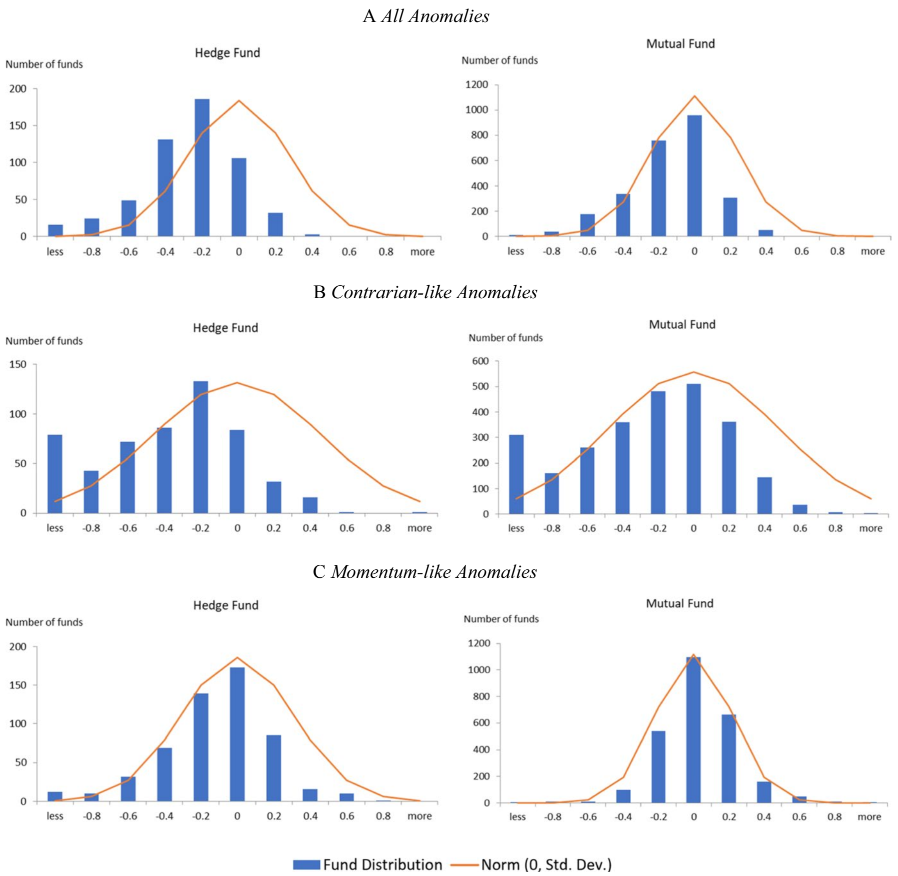


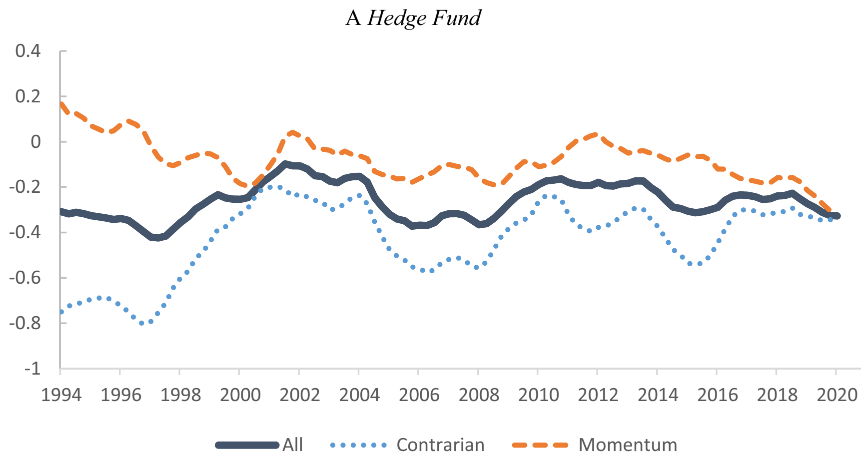
Fig. 3 Histogram of Excess Anomaly Decile Ranks for All, Momentum, and Contrarian Anomalies. This figure plots the distribution of fund-average excess anomaly decile ranks of stock holdings across all, momentum, and contrarian anomalies. We obtain mutual fund stock holdings from the Thomson Reuters Mutual Fund Holdings Database. We obtain hedge funds' quarterly stock holdings by merging TASS with the Thomson Reuters 13F database. For stock holdings analyses, the number of mutual funds is 2,800, and the number of hedge fund companies is 650. We define momentum- (contrarian-) like anomalies as those anomalies whose holding period returns and formation period returns are in the same (opposite) direction. There are 28 contrarian-like anomalies and 26 momentum-like anomalies in our sample. For each fund, we compute the average excess anomaly decile rank across all/contrarian-like/momentum-like anomalies. We then plot the distribution of the excess anomaly decile ranks across funds. The orange line in each graph shows a normal distribution with mean of zero and standard deviation equal to that of the actual distribution

anomalies persists over time. Fourth, there is large time-series variation in the excess anomaly ranks for both hedge funds and mutual funds. Finally, we find a modest level of co-movement in the excess anomaly ranks between hedge funds and mutual funds.

Fig. 4 Time Series of Excess Anomaly Decile Ranks by Anomaly Categories**.** This figure plots the time-series of fund-average excess anomaly decile ranks of stock holdings by anomaly categories. We obtain mutual fund stock holdings from the Thomson Reuters Mutual Fund Holdings Database. We obtain hedge funds' quarterly stock holdings by merging TASS with the Thomson Reuters 13F database. Our sample period is from 1994 to 2020. We group our sample anomalies by using the agglomerative clustering approach (Jensen et al. 2022; Murtagh and Legendre 2014). For each fund in each quarter, we compute the average excess anomaly decile rank across all anomalies in each category. We then plot the average across funds over time (four-quarter moving average)

4.5 Additional analyses and discussions

In this section, we perform several additional analyses to examine the sources and robustness of our results. In addition, we provide an analysis of anomaly timing skills. To conserve space, we present the detailed results of these analyses in the Internet Appendix.



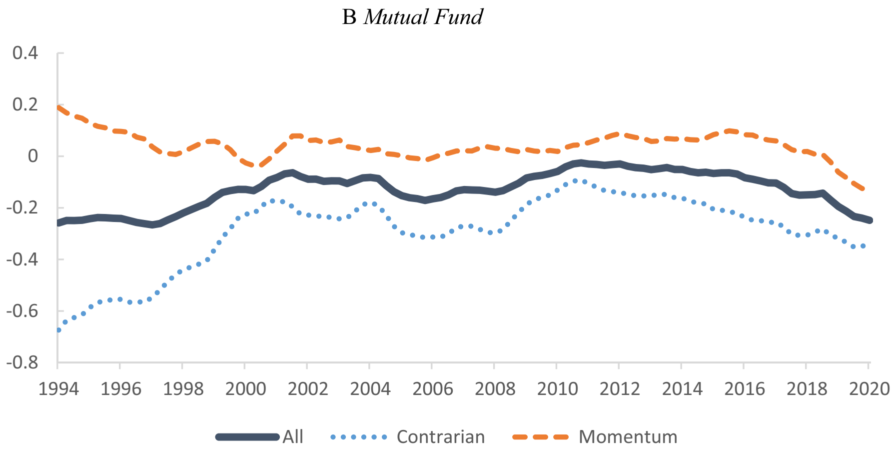


Fig. 5 Time Series of Excess Anomaly Decile Ranks for All, Momentum, and Contrarian Anomalies. This figure plots the time-series of fund-average excess anomaly decile ranks of stock holdings. We obtain mutual fund stock holdings from the Thomson Reuters Mutual Fund Holdings Database. We obtain hedge funds' quarterly stock holdings by merging TASS with the Thomson Reuters 13F database. We define momentum- (contrarian-) like anomalies as those anomalies whose holding period returns and formation period returns are in the same (opposite) direction. There are 28 contrarian-like anomalies and 26 momentum-like anomalies in our sample. For each fund, we compute the average excess anomaly decile rank across all/contrarian-like/momentum-like anomalies each quarter. We then plot the average across funds over time (four-quarter moving average). Panel A. Hedge Fund. Panel B. Mutual Fund

4.5.1 Financial crisis

We first investigate whether the negative loadings on accounting anomaly returns are concentrated during the 2007–2009 financial crisis period. It has been well documented that market liquidity and funding liquidity dried up during the financial crisis. As a consequence, hedge funds and mutual funds might have involuntarily unwound their positions and trade contrary to the prescriptions of the accounting anomalies during financial crisis. To test this possibility, we estimate the following regression:

$$r_t = \alpha + \beta LS_t + \gamma Financial\_Crisis_t \times LS_t + \boldsymbol{\theta}'\mathbf{X_t} + e_t \tag{4}$$

where r_t is the aggregate hedge fund or mutual fund return in month t and LS_t is the long-short return of the accounting anomaly in month t. Basically, we augment the regression Eq. (1) by adding an interaction term between the long-short return of the accounting anomaly and a dummy variable for the financial crisis period. To conserve space, we present the regression results in Table IA.2 of the Internet Appendix. Our results indicate that the loadings on anomaly returns are indeed somewhat lower during the 2007–2009 financial crisis. Nevertheless, the anomaly loadings continue to be disproportionately negative outside the financial crisis period, suggesting that our results are not driven by the financial crisis period.

4.5.2 Publication effect

Previous studies (e.g., McLean and Pontiff 2016) have shown that after the publication of the academic study that first documents the anomaly, the profitability of the anomaly trading strategy declines significantly, likely due to the growing awareness of the anomaly and increasing arbitrage activities (Calluzzo et al. 2019). Therefore, it is possible that the negative loadings are concentrated during the pre-publication period when investors were not aware of the anomaly. To examine this possibility, we regress aggregate fund returns on the long-short returns of the accounting anomaly and an interaction term between the post-publication dummy variable and the anomaly returns.

$$r_t = \alpha + \beta LS_t + \gamma Post\_Publication_t \times LS_t + \boldsymbol{\theta}'\mathbf{X_t} + e_t \tag{5}$$

Here, *Post_Publication* is a dummy variable that takes the value of 1 if month t is after the publication of the academic study that first documents the anomaly. Table IA.3 in the Internet Appendix presents the results of this analysis. Six of the 54 accounting anomalies were published before 1994, i.e., the beginning year of our sample period, so we cannot estimate regression Eq. (5) for these anomalies. Overall, we find little evidence that the negative loadings on anomaly returns are concentrated during the pre-publication period.

4.5.3 Fund flows

Prior studies document evidence that fund flows to hedge funds are smart and help attenuate anomalies, while flows to mutual funds are dumb and exacerbate market anomalies (Frazzini and Lamont 2008; Akbas et al. 2015). To investigate whether our results are influenced by fund flows, we estimate the following regression:

$$r_t = \alpha + \beta LS_t + \gamma Fund\_Flow_{t-1} \times LS_t + \boldsymbol{\theta}'\mathbf{X_t} + e_t \tag{6}$$

We compute fund flows by following the approach of Sirri and Tufano (1998). We then aggregate the flows across all hedge funds or mutual funds. We present the regression results in Table IA.4 of the Internet Appendix. Overall, we do not find a significant impact of fund flows on the anomaly loadings. After controlling for the effect of fund flows, we continue to find that the loadings on the long-short returns of accounting anomalies tend to be negative.

4.5.4 Timing skill

In this section, we examine whether fund managers are able to time anomaly returns. The long-short returns of accounting anomalies vary substantially over time and are sometimes negative. To test whether fund managers have timing skills, we regress future anomaly returns on temporal changes in excess anomaly ranks. If fund managers have timing ability, we would expect that they increase the anomaly decile ranks prior to high anomaly returns and decrease the anomaly ranks before low anomaly returns. That is, we expect the regression coefficient on the change in anomaly ranks to be positive. We perform the analysis at both the aggregate level and the individual fund level and present the results in Table IA.5 and Table IA.6 of the Internet Appendix, respectively. Overall, at both the aggregate level and fund level, we find little evidence that fund managers possess anomaly timing ability.[13] This finding should not be too surprising, considering that, if fund managers are sophisticated enough to time accounting anomalies, they should probably trade on accounting anomalies more actively than we have observed.

4.5.5 Who are the sophisticated investors?

If hedge funds and mutual funds do not actively exploit accounting anomalies, then who does? First of all, we would like to clarify that, although hedge funds and mutual funds, as a group, tend to trade contrary to anomaly prescriptions, this does not mean that all hedge funds and mutual funds trade against accounting anomalies. Indeed, our fund-level analysis indicates that a significant number of funds do trade on accounting anomalies and earn higher returns as a result. Second, we note that our hedge fund sample represents only a subset of the hedge fund universe. Unlike mutual funds, the majority of hedge funds, at least until recently, do not disclose their information either to the regulators or commercial data vendors. It is possible that many hedge funds not covered by the Lipper TASS database trade on accounting anomalies. Third, the literature has presented compelling evidence that short sellers, most of which are institutional investors, trade on anomalies (Drake et al.

[13] We also plot in Figure IA.2 the relation between temporal changes in excess anomaly ranks and subsequent anomaly returns and find that the relationship is largely flat, consistent with the results in Tables IA.5 and IA.6.

2011; McLean et al. 2020; Wang et al. 2020). Fourth, given their incentives and potential informational advantage, it is possible that proprietary traders, particularly those within financial conglomerates, are sophisticated and exploit accounting anomalies. Finally, although the recent literature has presented some evidence that retail investors are informed (e.g.,Kaniel et al. 2012; Kelley and Tetlock 2013, 2017), there is no conclusive evidence that retail investors are sophisticated enough to systematically trade on accounting anomalies.

5 Conclusions

We use the returns and stockholdings of a large sample of hedge funds and mutual funds along with a comprehensive sample of fundamental signals to examine the extent to which sophisticated investors follow fundamental analysis strategies. We find that the returns of hedge funds and mutual funds tend to load negatively on the long-short returns of 54 fundamental strategies. This finding persists after controlling for the publication effect, financial crisis, and fund flows. The negative anomaly loadings are driven primarily by the short leg of the anomalies, are more pronounced among contrarian-like anomalies, and are more prevalent among anomalies in the earnings quality, investment, profitability, external financing, value, and composite categories. We also find that funds with higher anomaly loadings significantly outperform their peers. Our results suggest that fund managers, as a group, do not systematically exploit the return predictability of accounting information, but a subset of fund managers are skilled and benefit from trading on accounting anomalies. We find similar results when examining the stockholdings of hedge funds and mutual funds. Our findings have important implications for the persistence of accounting anomalies, sophistication of institutional investors, and investment value of fundamental analysis. In particular, if accounting anomalies are driven by mispricing and sophisticated investors such as hedge funds and mutual funds do not systematically arbitrage against it, then these anomalies are less likely to disappear.

Appendix

List of 54 accounting anomalies

Abbreviation	Anomaly	Authors
Panel A: Earnings Quality		
TAcc	Total accruals	Richardson et al. (2005)
PTAcc	Percent total accruals	Hafzalla et al. (2011)
OAcc	Operating accruals	Sloan (1996)
POAcc	Percent operating accruals	Hafzalla et al. (2011)
AG	Growth in total assets	Cooper et al. (2008)
BrandCap	Brand capital-to-assets	Belo et al. (2014)
dSales	Sales growth	Lakonishok et al. (1994)
dBE	Growth in book equity	Lockwood and Prombutr (2010)
dOA	Growth in long-term operating assets	Fairfield et al. (2003)
dNCOA	Changes in net noncurrent operating assets	Richardson et al. (2005)
Panel B: Investment		
CI	Abnormal corporate Investment	Titman et al. (2004)
I/A	Investment-to-assets	Lyandres et al. (2008)
dInv	Investment growth	Xing (2008)
dInv_adj	Industry-adjusted growth in investment	Abarbanell and Bushee (1998)
IG	Inventory growth	Belo and Lin (2012)
dInvent	Inventory changes	Thomas and Zhang (2002)
NOA	Net operating assets	Hirshleifer et al. (2004)
Panel C: Profitability		
ROA	Return on assets	Balakrishnan et al. (2010)
ROE	Return on equity	Haugen and Baker (1996)
RNOA	Return on net operating assets	Soliman (2008)
GP/A	Gross profitability-to-assets	Novy-Marx (2013)
Cturn	Capital turnover	Haugen and Baker (1996)
OrgCap	Organizational capital-to-assets	Eisfeldt and Papanikolaou (2013)
OperLev	Operating leverage	Novy-Marx (2011)
PM	Profit margin	Soliman (2008)
Panel D: Profit Growth		
SUE	Earnings surprise	Foster et al. (1984)
RS	Revenue surprise	Jegadeesh and Livnat (2006)
TaxExp	Tax expense surprise	Thomas and Zhang (2011)
EAR	Abnormal returns around earnings announcements	Chan et al. (1996)
SA_SGA	Changes in sales minus changes in SG&A	Abarbanell and Bushee (1998)
SA_IV	Changes in sales minus changes in inventory	Abarbanell and Bushee (1998)
dNWC	Changes in net non-cash working capital	Richardson et al. (2005)

Abbreviation	Anomaly	Authors
dAturn	Changes in asset turnover	Soliman (2008)
dPM	Changes in profit margin	Soliman (2008)
Panel E: External Financing		
Xfin	Net external financing	Bradshaw et al. (2006)
NSI	Net stock issues	Pontiff and Woodgate (2008)
Payout	Payout yield	Boudoukh et al. (2007)
Npayout	Net payout yield	Boudoukh et al. (2007)
TI/BI	Taxable income-to-book income	Lev and Nissim (2004)
Panel F: R&D		
R&D/A	R&D capital-to-assets	Li (2011)
R&D/M	R&D-to-market	Chan et al. (2001)
Aturn	Asset turnover	Soliman (2008)
AccQ	Accrual quality	Francis et al. (2005)
Panel G: Value		
E/P	Earnings-to-price	Basu (1983)
CF/P	Cash flow-to-price	Lakonishok et al. (1994)
B/M	Book-to-market equity	Rosenberg et al. (1985)
A/M	Market leverage	Bhandari (1988)
S/P	Sales-to-price	Barbee et al. (1996)
AD/M	Advertisement expense-to-market equity	Chan et al. (2001)
Panel H: Composite		
F-score	F-score	Piotroski (2000)
G-score	G-score	Mohanram (2005)
PS	Updated F-score with B/M	Piotroski and So (2012)
LM	Updated F-score with V/P	Li and Mohanram (2019)
V/P	Fundamental value to price	Frankel and Lee (1998)

Our sample includes 54 anomalies constructed primarily using the Compustat data. We group our sample anomalies by using the agglomerative clustering approach (Jensen et al. 2022; Murtagh and Legendre 2014) and organize our panels by anomaly category.

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Data availability Data are available from the sources cited in the text.

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