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Institutional trading, news, and accounting anomalies

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ABSTRACT

Previous studies find mixed evidence on whether institutional investors exploit capital market anomalies. Examining a large sample of accounting-based anomalies, we find that institutions trade in the wrong direction of overreaction anomalies, but in the right direction of underreaction anomalies. These heterogenous trading patterns, rather than reflecting institutions' differential anomaly trading skills, can be simply explained by institutions' tendency to trade in the same direction as the sentiment of news. Examining earnings news and a comprehensive sample of newswire releases, we find strong support for this explanation. Finally, institutional trading appears to exacerbate (mitigate) mispricing associated with overreaction (underreaction) anomalies.

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1. Introduction

Prior literature has shown that many accounting variables, including earnings, cash flows, and accruals, predict the cross-section of stock returns (see e.g., Richardson et al. (2010) and Green et al. (2013)). The long-short returns to the trading strategies based on these accounting variables are economically large, highly statistically significant, and unlikely to be the result of data mining (Lewellen (2010) and Yan and Zheng (2017)). Although risk-based explanations exist (e.g., Khan (2008) and Penman and Zhu (2014)), most studies present evidence in favor of behavioral explanations and argue that the return predictability arises because the market fails to completely or correctly impound accounting information into prices (e.g., Bernard and Thomas (1989), Sloan (1996), Fairfield et al. (2003), and Balakrishnan et al. (2010)).

If the accounting anomalies are due to market inefficiency, then one would expect sophisticated investors such as institutional investors to arbitrage against the mispricing. A number of studies have investigated the issue and find mixed results. For example, Ke and Ramalingegowda (2005) show that transient institutions exploit the post-earnings-announcement-drift (PEAD). Ali et al. (2008) find that few, if any, mutual funds trade on the accruals anomaly.

In this paper, we re-examine how institutions trade with respect to accounting anomalies by classifying them into two

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categories—overreaction anomalies and underreaction anomalies. Intuitively, if the market mis-reacts to accounting information, then it could be either overreaction or underreaction. Lakonishok et al. (1994), for example, argue that the value anomaly arises because investors extrapolate past performance too far into the future (i.e., market overreaction). On the other hand, the PEAD is widely interpreted as evidence of market underreacting to earnings information (Bernard and Thomas (1989)). Using a clustering analysis, we classify 29 of our 56 sample anomalies as overreaction anomalies and the remaining 27 as underreaction anomalies.[1]

We follow Edelen et al. (2016) and measure institutional trading during the six quarters prior to the anomaly formation date. This choice allows us to examine "how institutions modify their portfolios as stocks take on anomaly-defining characteristics" (Edelen et al. (2016, p.473)). We construct two measures of institutional trading: Change in institutional ownership and percentage change in the number of institutional holders. For each anomaly, we compute institutional trading for stocks in the long and short legs separately and then take the difference between the two. This difference in institutional trading between the long leg and the short leg is our measure of anomaly trading, and, for ease of exposition, we refer to it as the net institutional trading. A positive net trading indicates that institutions are net buyers of the long leg relative to the short leg, i.e., they trade according to anomaly prescriptions. Conversely, a negative net trading indicates that institutions are net sellers of the long leg relative to the short leg, meaning that they trade contrary to anomaly prescriptions.

Our primary finding is that institutional investors exhibit diametrically opposite trading behaviors across overreaction and underreaction anomalies. Specifically, the net institutional trading is uniformly negative for overreaction anomalies and predominantly positive for underreaction anomalies. Using the first measure of institutional trading, i.e., change in institutional ownership, we find that the average net institutional trading is −2.47% (t-stat = −9.43) among overreaction anomalies, and is 1.59% (t-stat = 5.44) among underreaction anomalies. The net institutional trading is negative and statistically significant among all 29 overreaction anomalies, and is positive and significant among 21 of the 27 underreaction anomalies.

The results are qualitatively identical when we examine the second measure of institutional trading, i.e., percentage change in the number of institutional owners. The average net institutional trading is −15.33% (t-stat = −9.03) among overreaction anomalies, and is 9.26% (t-stat = 6.77) among underreaction anomalies. The net institutional trading is significantly negative among 28 of the 29 overreaction anomalies, and significantly positive among 21 of the 27 underreaction anomalies. Overall, our results indicate that institutions trade according to the prescriptions of underreaction anomalies, while trading contrary to the prescriptions of overreaction anomalies.

How do we interpret institutions' differential trading behaviors across underreaction and overreaction anomalies? At a simple level, one might interpret our findings as suggesting that institutions are skilled at exploiting underreaction anomalies, while possessing perverse trading skills on overreaction anomalies. This, however, begs the question why? If institutions are sophisticated enough to trade on one group of anomalies, they should be sophisticated enough to trade on another group of anomalies, or at least not trade against it.

We propose a simple and unified explanation for our findings. We argue that institutions' heterogenous trading behaviors across overreaction and underreaction anomalies, rather than reflecting institutions' differential anomaly trading skills, can be simply explained by institutional investors' tendency to trade in the same direction as the sentiment of news, i.e., buying stocks with good news and selling stocks with bad news.[2] For overreaction anomalies such as the value anomaly, stocks in the short leg (growth stocks) experience more good news during the anomaly formation period than stocks in the long leg (value stocks).[3] That is why institutions buy more of the short leg than the long leg. As a result, institutions appear to trade in the wrong direction of overreaction anomalies. Conversely, for underreaction anomalies, stocks in the long leg (e.g., more profitable firms) experience more good news than those in the short leg (e.g., less profitable firms) during the anomaly formation period. Consequently, institutions buy more of the long leg relative to the short leg, thus appearing to trade in the right direction of underreaction anomalies.

To test the above explanation, we examine earnings news and a comprehensive database of newswire releases. We report two main results. First, we find that institutional trading is significantly higher (i.e., more buying) among stocks with positive news than stocks with negative news, suggesting that institutions tend to trade in the direction of news. Second, consistent with our earlier argument, we find that stocks in the long (short) leg of overreaction anomalies tend to experience negative (positive) news during the anomaly formation period, while stocks in the long (short) leg of underreaction anomalies tend to experience positive (negative) news. The above two results combined together provide a natural explanation for our finding that institutions tend to trade in the wrong direction of overreaction anomalies, but in the right direction of underreaction anomalies.

Why do institutions tend to trade in the same direction as the sentiment of news? We offer several explanations. First, institutional investors, due to their fiduciary responsibility, may consider companies with good news as being more prudent than companies with bad news (Del Guercio (1996)). Second, the principal-agent conflict between the money managers and investors and the short-term evaluation period may induce money managers to favor stocks with superior recent performance (Lakonishok et al. (1994)). Third, institutions may buy (sell) stocks with good (bad) news for the purpose of window dressing (Lakonishok et al. (1991)). Fourth, institutional investors may believe that the market underreacts to news (Bernard and Thomas (1989, 1990)). Finally, institutional investors may over-extrapolate firms' past performance and trade accordingly (La Porta et al. (1997)).

[1] We use a K-means clustering model to group accounting anomalies into two clusters based on how similar their returns are. We refer the readers to Section 3.2 for more details on the K-means clustering model.

[2] For conciseness, we also use the phrase "trade in the direction of news".

[3] Lakonishok et al. (1994) an d La Porta et al. (1997), for example, show that growth stocks underperform value stocks because the market overreacts to good (bad) news about growth (value) stocks.

The prudent-man law explanation predicts that our finding should be stronger for banks and insurance companies than for investment companies and advisors. We fail to find such evidence. We find that our results are stronger for transient institutions than for dedicated investors, consistent with the agency and short-termism explanation. Using a transaction-level institutional trading database (i.e., the Ancerno database), we find little evidence that institutions engage in window dressing. Finally, we examine how institutions trade in response to earnings news during the quarter of the earnings announcement as well as the eight quarters subsequent to the earnings announcement and find supporting evidence for both the market underreaction and over-extrapolation explanations.

Exploiting accounting anomalies requires both buying winners and selling losers. Some institutions (e.g., mutual funds) are generally prohibited from short selling, while other institutions (e.g., hedge funds) face no such constraints. To investigate whether mutual funds and hedge funds exhibit different trading behaviors, we repeat our main analysis for mutual funds and hedge funds separately. The results for mutual funds and hedge funds are qualitatively similar to those for all institutions. Specifically, we find that both mutual funds and hedge funds tend to trade in the right (wrong) direction of underreaction (overreaction) anomalies.

A potential reason why we find similar results between mutual funds and hedge funds is that the 13F database contains only long positions. To mitigate this issue, we perform an analysis by using short interest as a proxy for the hedge funds' short positions. Examining the level of and change in short interest, we find that short sellers tend to trade in the right direction of both underreaction and overreaction anomalies. Combining the long positions of hedge funds with their short positions (as proxied by short interest) indicates that hedge funds continue to trade in the right direction of underreaction anomalies. However, there is no longer any significant evidence that hedge funds trade in the wrong direction of overreaction anomalies.

In our final empirical analysis, we examine anomaly long-short returns conditional on whether institutions trade in the right or wrong direction of an anomaly. Our analysis indicates that, for both overreaction and underreaction anomalies, an anomaly's subsequent long-short returns are significantly higher when institutions trade in the wrong direction of the anomaly. In fact, when institutions trade in the right direction of an anomaly during the formation period, subsequent anomaly returns are indistinguishable from zero. Given that institutions tend to trade in the wrong direction of overreaction anomalies and in the right direction of underreaction anomalies, our results are consistent with institutional trading aggravating overreaction anomalies, while alleviating underreaction anomalies.

If institutions tend to buy good news stocks and sell bad news stocks, then who are on the other side of their trades? We note that although institutional investors, as a group, tend to trade in the same direction as the sentiment of news, it does not mean that all institutions do. Indeed, our analysis indicates that dedicated investors tend to trade in the opposite direction of news. Institutional investors account for more than half of the equity ownership in the U.S. and an even greater share of total trading volume, so institutions routinely trade against each other. In addition, the literature has shown that short sellers are contrarians (Dechow et al. (2001) and Diether et al. (2009)), i.e., they short more when past returns are higher. Therefore, short sellers may trade contrary to the sentiment of news. Finally, it is possible that individual investors (e.g., Boehmer et al. (2021)) or small institutional investors that are not in the 13F database tend to trade in the opposite direction of news.[4]

Our paper contributes to the extensive literature examining the predictive ability of accounting information for future fundamentals and stock returns. Understanding the predictive content of accounting information is important for all users of financial statements (e.g., regulators, customers, and managements), especially for equity investors. In particular, the information contained in financial statements can help investors make better portfolio allocation decisions (Richardson et al. (2010)). We explore this issue by examining whether an important class of investors, namely institutional investors, exploit the predictive ability of accounting variables.

Our paper builds on Edelen et al. (2016), who show that institutions trade contrary to the prescriptions of seven capital market anomalies. We extend Edelen et al. (2016) by examining a comprehensive sample of accounting anomalies, which enables us to draw more general conclusions, and by classifying our sample anomalies into two distinct categories. Our primary contribution is to show that institutions exhibit opposite trading behaviors across overreaction and underreaction anomalies. We argue that the heterogenous trading patterns across overreaction and underreaction anomalies do not necessarily reflect institutions' differential anomaly trading skills. Rather, they can be explained by institutions' tendency to trade in the direction of news. Overall, our findings provide fresh insights into institutional trading behaviors and have important implications for the persistence of accounting anomalies, market efficiency, and institutional investor sophistication.

Our paper also contributes to several other streams of the literature. We add to the literature examining the influence of institutional investors on the magnitude, persistence, and disappearance of accounting anomalies (e.g., Green et al. (2011) and Kokkonen and Suominen (2015)). In particular, if institutions tend to trade contrary to the prescriptions of overreaction anomalies, then these anomalies are less likely to disappear. Our paper also contributes to the extensive literature on whether institutional investors are informed (e.g., Ke and Petroni (2004), Bushee and Goodman (2007), and Wang (2021)) by showing that institutions trade on underreaction anomalies, but do not systematically exploit overreaction anomalies.

The rest of this paper proceeds as follows. Section 2 discusses the related literature. Section 3 introduces our sample, data, and methodology. Section 4 presents our empirical results. Section 5 concludes.

[4] Institutions with less than \$100 million of equity holdings under discretion are not required to file 13F reports.

2. Related literature and hypothesis development

2.1. Literature review

Prior literature has uncovered a large number of accounting variables that predict future stock returns. For example, Sloan (1996) shows that accruals are negatively associated with future stock returns. Fairfield et al. (2003) find a negative relation between growth in long-term net operating assets and future stock returns. Bradshaw et al. (2006) document a negative relation between a measure of external financing and future stock returns. Thomas and Zhang (2011) find that seasonally differenced quarterly tax expense is positively related to future returns.[5]

A closely related literature investigates the value of fundamental analysis. Ou and Penman (1989) examine a large number of financial statement variables and extract a summary value measure that predicts the direction of future earnings and future stock returns. Abarbanell and Bushee (1998) find that weighted average ranks on changes in nine fundamental signals predict a firm's return. Piotroski (2000) constructs an *F*-score and shows that it significantly predicts future stock returns. Yan and Zheng (2017) show that many accounting variables are significant predictors of the cross-section of stock returns even after accounting for data mining.

Competing explanations for accounting anomalies fall into two categories. Behavioral explanations suggest that return predictability arises because the stock prices fail to completely or correctly impound available information. Alternatively, rational explanations suggest that the abnormal returns are compensation 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. On the other hand, Khan (2008) presents a risk-based explanation for the accruals anomaly. Penman and Zhu (2014) provide a framework as well as empirical evidence that the "anomalous" long-short returns associated with accounting variables are consistent with rational pricing.

A number of prior studies examine whether institutional investors exploit accounting anomalies. 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. However, those funds that do trade on accruals make significant profit net of actual transactions costs. Green et al. (2011) document that the long-short returns to the accruals anomaly have declined as a result of hedge funds deploying more capital to exploit the anomaly.

A number of finance papers examine whether institutional investors exploit market anomalies including accounting anomalies. For example, Griffin and Xu (2009) examine the stockholdings of hedge funds and show that hedge funds exhibit little ability to pick stock styles. Edelen et al. (2016) find that institutions have a strong tendency to buy stocks classified as overvalued (short leg of the anomaly) during the anomaly formation period. Calluzzo et al. (2019), however, show that institutional investors do trade on anomalies during the post-formation period, but only after they are published in academic journals.

2.2. Hypothesis development

There are several reasons why institutional investors might trade in the same direction as the sentiment of news, i.e., buying in response to good news and selling in response to bad news. First, institutional investors may believe that the market underreacts to news. As such, they will buy stocks with good news and sell stocks with bad news in order to profit from the market underreaction. For example, previous studies (e.g., Bernard and Thomas (1989, 1990)) have presented extensive evidence that the market underreacts to earnings news.

Second, institutional investors may over-extrapolate firms' past performance and trade accordingly. Lakonishok et al. (1994) and La Porta et al. (1997), for example, show that the value anomaly is largely due to investors extrapolating the past superior performance of growth stocks too far into the future. Bordalo et al. (2023) present evidence that investors over-extrapolate long-term earnings growth.

Third, institutional investors, due to their fiduciary responsibility, may consider companies with good news as being more prudent than companies with bad news (Del Guercio (1996)). Fourth, the principal-agent conflict between money managers and investors and the short-term evaluation period may induce money managers to favor stocks with superior recent performance, i.e., good news (Lakonishok et al. (1994)). Finally, institutions may buy (sell) stocks with good (bad) news for the purpose of window dressing (Lakonishok et al. (1991)).

H1. Institutional investors trade in the direction of news, i.e., buying in response to good news and selling in response to bad news.

To the extent that underreaction anomalies result from market underreaction, stocks with good news during the anomaly formation period (e.g., more profitable firms) will tend to outperform in the future, while stocks with bad news during the anomaly formation period (e.g., less profitable firms) will tend to underperform in the future.

The pattern is the opposite for overreaction anomalies. For overreaction anomalies, the positive anomaly returns result from price correction. Specifically, stocks with good news during the anomaly formation period (e.g., growth firms) will tend to underperform in

[5] We refer the readers to Appendix A for the complete list of 56 accounting anomalies used in our study.

the future because of market overreaction to good news. Similarly, stocks with bad news during the anomaly formation period (e.g., value stocks) will tend to outperform in the future because of market overreaction to bad news.

H2. For underreaction anomalies, stocks in the long leg experience more good news than those in the short leg during the anomaly formation period. For overreaction anomalies, stocks in the short leg experience more good news during the anomaly formation period than stocks in the long leg.

Combining H1 and H2 suggests that, for underreaction anomalies, institutions will tend to buy more long-leg stocks than short-leg stocks during the anomaly formation period. Thus, institutions tend to trade in the right direction of underreaction anomalies. By the same token, for overreaction anomalies, institutions will tend to buy more short-leg stocks than long-leg stocks during the anomaly formation period. Therefore, institutions tend to trade in the wrong direction of overreaction anomalies.

H3. During the anomaly formation period, institutions tend to trade in the right direction of underreaction anomalies and wrong direction of overreaction anomalies.

3. Data, sample, and methods

3.1. Data

We obtain stock data including returns, share price, SIC code, exchange code, share code, and shares outstanding from the Center for Research in Security Prices (CRSP), and quarterly and annual accounting data from COMPUSTAT. We obtain Fama and French (1996) three factors and the momentum factor from Kenneth French's website.[6] Our sample consists of NYSE, AMEX, and NASDAQ common stocks (with a CRSP share code of 10 or 11) with data necessary to compute anomaly variables and subsequent stock returns. We exclude all financial stocks (with a SIC code in the 6000s). Our sample period is 1982–2021.

We obtain institutional investors' quarterly stock holdings from the Thomson/Refinitiv 13F database. A 1978 amendment to the Securities and Exchange Act of 1934 requires all institutional investment managers with greater than $100 million equity securities under discretionary management to report their quarter-end stock positions that are over 10,000 shares or worth more than $200,000. We obtain institutional investor classifications from Brian Bushee's website.[7]

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. 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 the 13F filings with the asset management companies' names from Lipper TASS. To ensure accuracy, we require exact match of the names.

3.2. Accounting anomalies

To compile a comprehensive list of accounting-based anomalies, we start with the samples of anomalies from Green et al. (2013), Hou et al. (2015), and McLean and Pontiff (2016). We restrict our sample to anomaly variables that are continuous (rather than indicator variables) and can be constructed primarily using the COMPUSTAT data. Our final sample includes 56 anomalies. The detailed list and definitions of these anomalies are contained in Appendix A.

Following Edelen et al. (2016), we sort all sample stocks into terciles based on each anomaly variable and construct long-short portfolios.[8] We examine the strategy that goes long on stocks in the top tercile and shorts stocks in the bottom tercile, where the top (bottom) tercile includes the stocks that are expected to outperform (underperform) after portfolio formation based on prior literature. We compute the long-short return as the difference between the return of the long-leg portfolio and the return of the short-leg portfolio.

As stated earlier, previous studies find that the predictability of accounting variables for future stock returns is due to the market failing to correctly incorporate accounting information into prices. If the market mis-reacts to accounting information, then, in principle, it either underreacts or overreacts. Rather than relying on subjective classifications, we employ a clustering analysis to classify our sample anomalies into underreaction or overreaction anomalies. Doing so minimizes our own discretion. We hypothesize that the long-short returns of an underreaction anomaly will be more similar to the long-short returns of other underreaction anomalies and less similar to the long-short returns of overreaction anomalies, and vice versa.

Specifically, we use a K-means clustering model to group our sample anomalies into clusters based on standardized long-short anomaly returns.[9] The main goal of K-means clustering model is to partition data points into a specified number of clusters based on similarity, namely by minimizing the within-cluster sum of squares (variance). In our context, we group anomalies based on the similarity of their returns. We implement the model by using the SAS procedure FASTCLUS, which combines an effective method for finding initial clusters with a standard iterative algorithm for minimizing the sum of squared distances from the cluster means. The

[6] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[7] https://accounting-faculty.wharton.upenn.edu/bushee/. We thank Brian Bushee for making the data available.

[8] Our results are qualitatively the same if we sort stocks into quintiles and construct long-short portfolios using the two extreme quintile portfolios.

[9] We standardize long-short returns by subtracting their mean and then dividing by the standard deviation. It is common practice to use standardized variables in K-means clustering models.

procedure uses a method called nearest centroid sorting. Specifically, a set of cluster seeds are selected as a first guess of the cluster centers (or means). Each observation is assigned to the nearest seed to form temporary clusters. The seeds are then replaced by the means of the temporary clusters, and the process is repeated until convergence is achieved.

Untabulated results indicate that, according to the cubic clustering criterion, $K = 2$, i.e., two clusters, is indeed optimal for our sample. We report the detailed results for the clustering analysis in Appendix A, which lists the 29 anomalies in the first cluster and the 27 anomalies in the second cluster. Recall that in the K-means model the clusters are chosen to minimize the sum of squared distance from the cluster centers. Therefore, the best way to show what characterizes the two clusters is to examine the anomalies that are the closest to the centers of these two clusters.

We find that the anomalies closest to the center of the first cluster are book-to-market, cash flow to price, and sales to price. These anomalies can be broadly characterized as value anomalies, i.e., they are all of the form V/P, just with different measures of V. In contrast, anomalies closest to the center of the second cluster are return on assets, failure probability, and gross profitability. These anomalies are closely related to various measures of profitability. Because value anomalies are commonly interpreted as evidence consistent with market overreaction (Lakonishok et al. (1994)), while profitability-based anomalies (e.g., Balakrishnan et al. (2010)) are commonly viewed as evidence of market underreaction, we label the first cluster as "overreaction anomalies" and the second cluster as "underreaction anomalies".

3.3. Measures of institutional trading

We follow Edelen et al. (2016) and compute institutional trading during the anomaly formation period, which, as stated earlier, is the six quarters prior to the anomaly formation date.[10] Similar to Edelen et al. (2016), we are primarily interested in examining how institutions change their portfolios as stocks take on anomaly characteristics. It is important to note that the information about the anomaly variables is publicly released during the formation period. For example, anomalies based on annual Compustat variables in year t have a formation date of June 30 of year $t+1$. Firms with a December fiscal year-end are required to file their annual reports by March 30 of year $t+1$, three months before the anomaly formation date. Firms with a fiscal year ending in the other months file even sooner. As such, institutional investors have ample opportunities to trade on the anomalies during the anomaly formation period.

We construct two measures of aggregate institutional trading. The first is the change in institutional ownership, where institutional ownership is calculated as the total number of shares held by all institutions divided by the total number of shares outstanding. This is the most commonly used measure of institutional trading. We also construct a second measure of institutional trading, i.e., the percentage change in the number of institutional holders. This measure focuses exclusively on new and closed positions and does not include adjustments to ongoing positions.

As stated earlier, we compute institutional trading during the anomaly formation period, i.e., the six quarters prior to the anomaly formation date. For each anomaly and each quarter during the formation period, we compute institutional trading for stocks in the long and short legs separately. We then sum the institutional trading across the six quarters during each formation period. We compute the difference in institutional trading between the long leg and the short leg and refer to this difference as the net institutional trading, which is our measure of anomaly trading.

4. Empirical results

4.1. Baseline results

We begin our analysis by examining how institutions trade with respect to our sample anomalies during the anomaly formation period. To conserve space, we provide a summary of the results for overreaction and underreaction anomalies in Table 1 and report the detailed anomaly-by-anomaly result in Table IA.2 in the Internet Appendix. The two panels of Table 1 contain the results for the two institutional trading measures.

By construction (i.e., the K-means clustering model), anomalies within the same cluster are correlated with each other.[11] As such, standard t-statistics for the mean institutional trading across anomalies may be overstated. We overcome this issue in two ways. First, we compute the average institutional trading across overreaction (or underreaction) anomalies for each time period and then report the time-series average of these cross-anomaly averages. We conduct our statistical inference based on the *time-series* standard deviation of these cross-sectional averages, while adjusting for possible heterogeneity and serial correlation by using Newey-West adjusted standard errors. Second, in addition to the average net institutional trading across anomalies, we also report the number of anomalies with a positive (or negative) net institutional trading as well as the number of anomalies with a significantly positive (or negative) net institutional trading.

Panel A presents the results for the first institutional trading measure, i.e., change in institutional ownership. Focusing on the overreaction anomalies, we find that institutional investors on average purchase 0.98% of the shares outstanding of the stocks in the

[10] As a robustness test, we also examine institutional trading during the anomaly holding period, i.e., during the two or four quarters after the anomaly formation date. See Table IA.4 in the Internet Appendix for more details.

[11] We report the correlations of anomaly returns and correlations of institutional trading across anomalies in Table IA.1 in the Internet Appendix. We find that the anomalies within the same cluster are on average positively correlated with each other, with the average correlation ranging from 0.16 to 0.46.

Table 1
Institutional trading on accounting anomalies.

Panel A: Change in Institutional Ownership								
	Long	Short	L-S	*t*-stat	# > 0	# ≫ 0	# < 0	# ≪ 0
Overreaction	0.98%	3.45%	−2.47%	−9.43	0	0	29	29
Underreaction	3.07%	1.48%	1.59%	5.44	22	21	5	4
Panel B: Percent Change in # of Institutional Owners								
	Long	Short	L-S	*t*-stat	# > 0	# ≫ 0	# < 0	# ≪ 0
Overreaction	6.54%	21.86%	−15.33%	−9.03	0	0	29	28
Underreaction	19.08%	9.82%	9.26%	6.77	22	21	5	3

This table reports institutional trading in anomaly portfolios during the formation period across 56 accounting anomalies. The list and definitions of the anomalies are contained in Appendix A. We obtain monthly stock data from the CRSP and accounting data from Compustat. Quarterly institutional holdings are from Thomson/Refinitiv 13F data. Our sample consists of NYSE, AMEX, and NASDAQ common stocks (with a CRSP share code of 10 or 11). We exclude financial stocks. We sort all sample stocks into terciles based on each anomaly variable. Stocks in the long (short) portfolio are expected to outperform (underperform) according to prior literature. The formation period is the six quarters preceding the anomaly formation date. We use a K-means clustering model to classify our sample anomalies into two categories, overreaction anomalies and underreaction anomalies. Change in institutional ownership is the change in percentage of shares held by institutions. Percent change in the number of institutional owners is the change in the logarithm of the number of institutional owners. The anomaly formation date is June 30 of each year. The *t*-statistics for the differences between the long and short legs are calculated using the Newey-West standard errors. "#>0", "#≫0", "#<0", and "#≪0" denote the number of anomalies where the long-short difference in institutional trading is positive, positive and significant at the 5% level, negative, and negative and significant at the 5% level, respectively. Our sample period is from 1982 to 2021.

long leg, while buying 3.45% of the stocks in the short leg. The average institutional trading is positive for both long and short legs (this is also the case for underreaction anomalies) because institutional ownership has increased significantly during our sample period. The net institutional trading, i.e., the difference between the long leg and the short leg, is −2.47%, with a *t*-statistic of −9.43. Moreover, we find that all 29 overreaction anomalies exhibit a negative and statistically significant net institutional trading. That is, we find that the net institutional trading is overwhelmingly negative for overreaction anomalies.

In contrast, we find that the net institutional trading is predominantly positive for underreaction anomalies. The average net institutional trading is 1.59% (*t*-stat = 5.44) among underreaction anomalies. In addition, 21 of the 27 underreaction anomalies have a positive and statistically significant net institutional trading. Overall, the results in Panel A suggest that institutions, as a group, tend to trade in the right direction of underreaction anomalies, but in the wrong direction of overreaction anomalies.[12]

Panel B reports the results for the percentage change in the number of institutional owners. This second measure of institutional trading focuses only on entry and exit trades by institutional investors. The results in Panel B are qualitatively similar to those in Panel A. We again find a big contrast between overreaction anomalies and underreaction anomalies. The average net institutional trading is −15.33% (*t*-stat = −9.03) among overreaction anomalies, and is 9.26% (*t*-stat = 6.77) among underreaction anomalies. The net institutional trading is negative among all 29 overreaction anomalies, 28 of which are statistically significant, and is positive and significant among 21 of the 27 underreaction anomalies. Overall, the results in Table 1 indicate that while institutional trading tends to agree with the predictions of underreaction anomalies, it tends to contradict the prescriptions of overreaction anomalies.

4.2. Institutional trading and news

At a simple level, one might interpret our finding as suggesting that institutions are skilled at exploiting underreaction anomalies, but have perverse trading skills for overreaction anomalies. The immediate follow-up question is why. Why do institutions exhibit opposite trading skills across underreaction and overreaction anomalies? If institutions are sophisticated enough to exploit one set of anomalies, shouldn't they be sophisticated enough to trade on another set of anomalies? Limits to arbitrage could potentially explain why institutions are reluctant to trade on certain anomalies, but cannot explain why they trade against anomalies. According to Shleifer and Vishny (1997), constrained institutions should at least trade in the right direction.

We propose a simple and unified explanation for our findings. We argue that the heterogenous trading behaviors of institutions across overreaction and underreaction anomalies can be simply explained by their tendency to trade in the direction of news, i.e., buying stocks with good news and selling stocks with bad news. For overreaction anomalies, stocks in the short-leg are more likely to have experienced good news during the anomaly formation period. For example, growth stocks exhibit more good news during the formation period than value stocks (Lakonishok et al. (1994) and La Porta et al. (1997)). Thus, if institutions buy more of good news stocks (i.e., growth stocks) than bad news stocks (i.e., value stocks), they would be trading contrary to the prescriptions of the value anomaly.

In contrast, stocks in the long-leg of underreaction anomalies (e.g., firms with higher profitability) tend to have more favorable news than stocks in the short-leg (e.g., firms with lower profitability) during the anomaly formation period. If institutional investors

[12] Our results indicate that institutions, in the aggregate, trade in the wrong direction of overreaction anomalies. This, however, does not preclude the possibility that *some* institutions trade in the right direction of overreaction anomalies.

chase stocks with positive news, they would buy more of high-profitability stocks than low-profitability stocks, i.e., trading in the right direction of the profitability anomaly. In short, institutional investors' propensity to trade in the direction of news can explain why institutional trading tends to contradict the prescriptions of overreaction anomalies, while agreeing with the predictions of underreaction anomalies.

To provide evidence on the above explanation, we examine two measures of news, with the first based on earnings news and the second based on newswire releases. The earnings news is measured by the standardized unexpected earnings (SUE).[13] Positive SUEs are considered as good news, while negative SUEs are considered as bad news.[14] To avoid any confounding effect, we remove the PEAD anomaly from our analysis of earnings news.

We also examine a comprehensive sample of newswire releases obtained from Thomson Reuters News Analytics (TRNA). TRNA captures a wide range of news articles from mainstream newspapers and social media, and it conducts a lexical analysis on the content of the news. For each news article, TRNA provides a rating on relevance and a rating on sentiment. Relevance indicates how relevant the news is to the company. Its value ranges from 0 to 1, where 1 corresponds to the highest relevance. Sentiment refers to whether the news item talks about the firm in a positive, neutral, or negative manner. We select news items with a relevance score of 1 to ensure that the news is directly related to the firm. We match firms covered in TRNA with the stocks in CRSP by using ticker symbols. For each stock in each quarter, we count the total number of news articles, the total number of news articles with positive sentiment (good news), and the total number of news articles with negative sentiment (bad news). Our main variable, *NetNews*, is defined as the difference between the number of good news and the number of bad news scaled by the total number of news. The sample period for the TRNA data is 2003–2018.

Panel A of Table 2 examines the relation between SUE and institutional trading. Specifically, we compute the average institutional trading each quarter separately for stocks with positive (or negative) SUE. We then calculate the difference in the average institutional trading between stocks with positive earnings news and stocks with negative earnings news. As in previous analyses, we employ two measures of institutional trading. Our results indicate that the average institutional trading is significantly higher (i.e., more buying) among stocks with positive SUE than among stocks with negative SUE. The results are highly significant regardless of which institutional trading measure we use. Our finding is consistent with Lang and McNichols (1997) and suggests that institutions tend to trade in the direction of earnings news.

Panel B of Table 2 reports the average SUE during the formation period for stocks in the long and short legs of overreaction and underreaction anomalies. We find that stocks in the long (short) leg of overreaction anomalies tend to exhibit negative (positive) SUE, while stocks in the long (short) leg of underreaction anomalies tend to exhibit positive (negative) SUE. These results are consistent with our earlier argument that stocks in the short leg of overreaction anomalies tend to experience more good news than stocks in the long leg during the anomaly formation period, while stocks in the long leg of underreaction anomalies tend to exhibit more good news than stocks in the short leg. This finding, combined with that in Panel A, helps explain why institutions tend to trade in the wrong direction of overreaction anomalies and in the right direction of underreaction anomalies.

Table 3 presents the results for the TRNA news. Similar to Table 2, we first examine the relation between *NetNews* and institutional trading in Panel A. Recall that *NetNews* is defined as the difference between the number of good news and the number of bad news scaled by the total number of news. Our results indicate that there is significantly more institutional buying of stocks with positive *NetNews* than stocks with negative *NetNews*. The results are highly significant for both institutional trading measures we use. This finding suggests that institutions tend to trade in the direction of news.

Panel B of Table 3 reports the average *NetNews* across the long and short legs of overreaction and underreaction anomalies during the formation period. We find that *NetNews* is on average positive. More importantly, stocks in the long leg of overreaction anomalies tend to exhibit higher *NetNews* than those in the short leg, while stocks in the long leg of underreaction anomalies tend to exhibit lower *NetNews* than the short leg. This finding again supports our earlier argument that stocks in the short leg of overreaction anomalies tend to experience more good news than stocks in the long leg during the formation period, while stocks in the long leg of underreaction anomalies tend to exhibit more good news than stocks in the short leg.

Overall, using both earnings news and newswire releases, we find strong evidence that institutions tend to trade in the same direction as the sentiment of news. We also find that stocks in the long (short) leg of overreaction anomalies tend to exhibit negative (positive) news during the anomaly formation period, while stocks in the long (short) leg of underreaction anomalies tend to exhibit positive (negative) news. These two results combined together explain the primary finding of our paper, i.e., institutions tend to trade in the wrong direction of overreaction anomalies and in the right direction of underreaction anomalies.

4.3. Mutual funds, hedge funds, and short sellers

Exploiting accounting anomalies requires not only buying winners but also selling losers. Some institutions, e.g., mutual funds, are generally prohibited from short selling. In contrast, hedge funds regularly take short positions. In this section, we examine whether

[13] We calculate SUE as follows. We first compute the unexpected earnings as the difference between current-quarter earnings per share (EPS) and the EPS four quarters ago. We then scale this difference by the standard deviation of unexpected earnings during the past eight quarters. We obtain quarterly earnings from Compustat.

[14] Our results are qualitatively identical if we use earnings surprise (actual earnings minus the analyst earnings forecast from IBES) as our measure of earnings news. See Table IA.3 in the Internet Appendix. We report the results for SUE in the main paper because of the longer sample period for the SUE data.

Table 2
Institutional trading and SUE.

Panel A: Institutional Trading and SUE

	SUE >0	SUE <0	Difference
Change in institutional ownership	0.49% (6.00)	0.06% (0.66)	0.43% (9.37)
Percentage change in # of institutional owners	3.62% (7.97)	0.08% (0.20)	3.54% (11.98)

Panel B: SUE for Anomaly Portfolios

	Long	Short	L-S	*t*-stat	# > 0	# ≫ 0	# < 0	# ≪ 0
Overreaction	−0.10	0.40	−0.50	−9.40	0	0	29	27
Underreaction	0.39	−0.15	0.54	6.18	23	22	3	2

This table examines the relation between earnings news and institutional trading in 55 accounting anomalies. The list and definitions of the anomalies are contained in Appendix A. We removed the PEAD anomaly to avoid confounding effect. We obtain monthly stock data from the CRSP and accounting data from Compustat. Quarterly institutional holdings are from Thomson/Refinitiv 13F data. Our sample consists of NYSE, AMEX, and NASDAQ common stocks (with a CRSP share code of 10 or 11). We exclude financial stocks. We sort all sample stocks into terciles based on each anomaly variable. Stocks in the long (short) portfolio are expected to outperform (underperform) according to prior literature. SUE is the difference between current-quarter earnings per share (EPS) and the EPS four quarters ago, scaled by the standard deviation of unexpected earnings during the past eight quarters. The formation period is the six quarters preceding the anomaly formation date. We use a K-means clustering model to classify our sample anomalies into two categories, overreaction anomalies and underreaction anomalies. Change in institutional ownership is the change in percentage of shares held by institutions. Percent change in the number of institutional owners is the change in the logarithm of the number of institutional owners. The *t*-statistics for the differences between the long and short legs are calculated using the Newey-West standard errors. "#>0", "#≫0", "#<0", and "#≪0" denote the number of anomalies where the long-short difference in institutional trading is positive, positive and significant at the 5% level, negative, and negative and significant at the 5% level, respectively. Our sample period is from 1982 to 2021.

Table 3
Institutional trading and Newswire Releases.

Panel A: Institutional Trading and NetNews

	NetNews > 0	*NetNews* < 0	Difference
Change in institutional ownership	0.55% (2.95)	0.18% (0.79)	0.37% (7.20)
Percentage change in # of institutional owners	2.85% (4.14)	0.44% (0.47)	2.41% (9.37)

Panel B: NetNews for Anomaly Portfolios

	Long	Short	L-S	*t*-stat	# > 0	# ≫ 0	# < 0	# ≪ 0
Overreaction	0.17	0.22	−0.05	−8.95	1	0	28	26
Underreaction	0.22	0.17	0.05	7.72	23	21	4	2

This table examines the relation between news and institutional trading in 56 accounting anomalies. The list and definitions of the anomalies are contained in Appendix A. We obtain a comprehensive sample of newswire releases from Thomson Reuters News Analytics (TRNA). We select the news items with a relevance score of 1. We match the firms in TRNA with the stocks in CRSP through tickers. For each stock, we count the total number of news articles and the total number of news articles with positive and negative sentiment in a given quarter. *NetNews* is defined as the total number of good news minus the total number of bad news and then scaled by the total number of news. The sample period for TRNA is 2003–2018.We obtain monthly stock data from the CRSP and accounting data from Compustat. Quarterly institutional holdings are from Thomson/Refinitiv 13F data. Our sample consists of NYSE, AMEX, and NASDAQ common stocks (with a CRSP share code of 10 or 11). We exclude financial stocks. We sort all sample stocks into terciles based on each anomaly variable. Stocks in the long (short) portfolio are expected to outperform (underperform) according to prior literature. The formation period is the six quarters preceding the anomaly formation date. We use a K-means clustering model to classify our sample anomalies into two categories, overreaction anomalies and underreaction anomalies. Change in institutional ownership is the change in percentage of shares held by institutions. Percent change in the number of institutional owners is the change in the logarithm of the number of institutional owners. The *t*-statistics for the differences between the long and short legs are calculated using the Newey-West standard errors. "#>0", "#≫0", "#<0", and "#≪0" denote the number of anomalies where the long-short difference in institutional trading is positive, positive and significant at the 5% level, negative, and negative and significant at the 5% level, respectively.

mutual funds and hedge funds exhibit different trading behaviors on accounting anomalies. As in Table 1 for all 13F institutions, we examine mutual fund and hedge fund trading during the anomaly formation period on long- and short-leg stocks for underreaction and overreaction anomalies. We report the results in Table 4. Panels A and B report the results for mutual funds, while Panels C and D present the results for hedge funds.

In Panel A, using the first institutional trading measure, we find that the net mutual fund trading, i.e., the difference in trading between the long leg and the short leg, is −0.77% (t-stat = −4.49) for overreaction anomalies. Moreover, 28 of 29 overreaction anomalies exhibit a negative and statistically significant net mutual fund trading. In contrast, we find that the net mutual fund trading is predominantly positive for underreaction anomalies. The average net mutual fund trading is 0.55% (*t*-stat = 4.54) among underreaction anomalies. In addition, 21 of the 27 underreaction anomalies have a positive and statistically significant net institutional trading. The results in Panel B for the second measure of institutional trading are qualitatively similar. Overall, mutual funds tend to trade in the right direction of underreaction anomalies, but in the wrong direction of overreaction anomalies.

Table 4
Institutional trading on accounting anomalies – Mutual Funds and Hedge Funds.

Panel A: Change in Institutional Ownership – Mutual Funds								
	Long	Short	L-S	*t*-stat	# > 0	# ≫ 0	# < 0	# ≪ 0
Overreaction	−0.23%	0.54%	−0.77%	−4.49	0	0	29	28
Underreaction	0.41%	−0.14%	0.55%	4.54	22	21	5	2
Panel B: Percent Change in # of Institutional Owners – Mutual Funds								
	Long	Short	L-S	*t*-stat	# > 0	# ≫ 0	# < 0	# ≪ 0
Overreaction	6.76%	17.37%	−10.61%	−7.90	3	1	26	24
Underreaction	18.17%	4.95%	13.22%	6.86	22	22	5	1
Panel C: Change in Institutional Ownership – Hedge Funds								
	Long	Short	L-S	*t*-stat	# > 0	# ≫ 0	# < 0	# ≪ 0
Overreaction	0.38%	0.73%	−0.34%	−4.81	2	0	27	25
Underreaction	0.71%	0.43%	0.28%	4.03	23	20	4	1
Panel D: Percent Change in # of Institutional Owners – Hedge Funds								
	Long	Short	L-S	*t*-stat	# > 0	# ≫ 0	# < 0	# ≪ 0
Overreaction	5.68%	14.51%	−8.82%	−9.04	1	0	28	26
Underreaction	14.10%	5.82%	8.27%	7.01	22	21	5	1

This table reports mutual fund and hedge fund trading in anomaly portfolios during the formation period across 56 accounting anomalies. The list and definitions of the anomalies are contained in Appendix A. We obtain monthly stock data from the CRSP and accounting data from Compustat. Mutual fund stock holdings are from Thomson/Refinitiv. Quarterly institutional holdings are from Thomson/Refinitiv 13F data. We identify hedge fund companies by manually matching the institutional investors' names from 13F with the asset management companies' names from Lipper TASS. Our sample consists of NYSE, AMEX, and NASDAQ common stocks (with a CRSP share code of 10 or 11). We exclude financial stocks. We sort all sample stocks into terciles based on each anomaly variable. Stocks in the long (short) portfolio are expected to outperform (underperform) according to prior literature. The formation period is the six quarters preceding the anomaly formation date. We use a K-means clustering model to classify our sample anomalies into two categories, overreaction anomalies and underreaction anomalies. Change in institutional ownership is the change in percentage of shares held by institutions. Percent change in the number of institutional owners is the change in the logarithm of the number of institutional owners. The anomaly formation date is June 30 of each year. The *t*-statistics for the differences between the long and short legs are calculated using the Newey-West standard errors. "#>0", "#≫0", "#<0", and "#≪0" denote the number of anomalies where the long-short difference in institutional trading is positive, positive and significant at the 5% level, negative, and negative and significant at the 5% level, respectively. Our sample period is from 1982 to 2021.

The results for hedge funds are similar to those for mutual funds. Using the first institutional trading measure, we find that the net hedge fund trading is −0.34% (*t*-stat = −4.81) for overreaction anomalies. Moreover, 25 of 29 overreaction anomalies exhibit a negative and statistically significant net hedge fund trading. In contrast, the net hedge fund trading is predominantly positive for underreaction anomalies. The average net hedge fund trading is 0.28% (t-stat = 4.03) among underreaction anomalies. In addition, 20 of the 27 underreaction anomalies have a positive and statistically significant net institutional trading. The results for the second measure of institutional trading are qualitatively similar. Overall, we show that hedge funds also tend to trade in the right direction of underreaction anomalies, but in the wrong direction of overreaction anomalies.

The results for hedge funds, however, are based only on the long position of hedge funds. Hedge funds are known to be active short sellers. Do hedge funds exhibit different trading behaviors in their short positions? To answer this question, we use the short interest as a proxy for the shorting positions of hedge funds. We obtain the semi-monthly short interest from Compustat. We note that the short interest data for NASDAQ stocks begins in late 2003, so the sample period for our short interest analysis is 2004–2021. To ensure consistency with our analysis based on quarterly institutional holdings, we convert the semi-monthly short interest to the quarterly frequency by using the last short interest reported for each quarter. We perform two analyses using the quarterly short interest. First, we examine the change in short interest for long- and short-leg stocks during the anomaly formation period for underreaction and overreaction anomalies. Second, we also examine the level of short interest for long- and short-leg stocks of underreaction and overreaction anomalies. We present the results for changes in short interest in Panel A of Table 5 and the results for the level of short interest in Panel B.

In Panel A, we find that, for both underreaction and overreaction anomalies, the change in short interest is positive for both long and short legs, which simply reflects the fact that short interest has increased significantly over our sample period. More importantly, we find that the difference in changes in short interest between the long and short legs is negative for both overreaction anomalies and underreaction anomalies, suggesting that the short interest increases more for short-leg stocks than for long-leg stocks. In Panel B, we find that the difference in the level of short interest between long and short legs is negative for both underreaction anomalies and overreaction anomalies, suggesting that the short-leg stocks are more heavily shorted than the long-leg stocks. Overall, we find that short sellers tend to trade in the right direction of both underreaction and overreaction anomalies. The results on overreaction anomalies, in particular, are in contrast to the results based on the long positions (from the 13F database), where we find that institutions tend to trade in the wrong direction of overreaction anomalies. Our findings suggest that short sellers are informed, and that they exploit accounting anomalies.

An interesting question is what happens if we combine the long positions of hedge funds with their short positions as proxied by

Table 5
Short interest and accounting anomalies.

	Long	Short	L-S	*t*-stat	# > 0	# ≫ 0	# < 0	# ≪ 0
Panel A: Change in Short Interest								
Overreaction	0.51%	0.88%	−0.37%	−3.30	5	2	24	18
Underreaction	0.64%	0.80%	−0.16%	−1.27	9	2	18	8
Panel B: Level of Short Interest								
	Long	Short	L-S	*t*-stat	# > 0	# ≫ 0	# < 0	# ≪ 0
Overreaction	5.06%	5.45%	−0.39%	−1.94	7	3	22	16
Underreaction	5.08%	5.39%	−0.31%	−1.63	5	2	22	9
Panel C: Changes in net hedge fund ownership (long position - short interest)								
	Long	Short	L-S	*t*-stat	# > 0	# ≫ 0	# < 0	# ≪ 0
Overreaction	−0.47%	−0.35%	−0.12%	−1.10	12	7	17	11
Underreaction	−0.19%	−0.63%	0.44%	5.78	25	14	2	0

This table examines short interest of anomaly portfolios during the formation period across 56 accounting anomalies. The list and definitions of the anomalies are contained in Appendix A. We obtain monthly stock data from the CRSP and accounting data from Compustat. Short interest data are from Compustat. Our sample consists of NYSE, AMEX, and NASDAQ common stocks (with a CRSP share code of 10 or 11). We exclude financial stocks. We sort all sample stocks into terciles based on each anomaly variable. Stocks in the long (short) portfolio are expected to outperform (underperform) according to prior literature. The formation period is the six quarters preceding the anomaly formation date. We use a K-means clustering model to classify our sample anomalies into two categories, overreaction anomalies and underreaction anomalies. Change in institutional ownership is the change in percentage of shares held by institutions. The anomaly formation date is June 30 of each year. The *t*-statistics for the differences between the long and short legs are calculated using the Newey-West standard errors. "#>0", "#≫0", "#<0", and "#≪0" denote the number of anomalies where the long-short difference in institutional trading is positive, positive and significant at the 5% level, negative, and negative and significant at the 5% level, respectively. The sample period is from 2004 to 2021.

short interest.[15] To address this question, we perform an analysis of hedge funds' combined long and short positions in Panel C. Our results indicate that hedge funds continue to trade in the right direction of underreaction anomalies. Specifically, the average net hedge fund trading is 0.44% (t-stat = 5.78) for underreaction anomalies. However, the average net hedge fund trading is statistically insignificant for overreaction anomalies. This finding suggests that once we combine the long and short positions of hedge funds, there is no longer significant evidence that hedge funds trade in the wrong direction of overreaction anomalies.

4.4. *Sub-periods*

4.4.1. *Before and after publication*

We have shown that institutions tend to trade in the wrong direction of overreaction anomalies. It is possible that such trading behavior is concentrated during the period before an anomaly is published in academic journals. After an anomaly is widely publicized, institutions may trade more actively on the anomaly. To explore this possibility, we identify the publication year of each anomaly in our sample and repeat our analysis separately for pre- and post-publication periods. For brevity, we present the results in Table IA.5 in the Internet Appendix. Overall, we find little evidence of a publication effect. During both pre- and post-publication periods, institutions trade in the opposite direction of overreaction anomalies and in the right direction of underreaction anomalies.[16]

4.4.2. *Before and After 2004*

Green et al. (2011) argue that around 2004 many academics left to pursue accounting related trading strategies in asset management firms. To test if this impacts institutional trading behaviors, we repeat our main analysis before and after 2004. For brevity, we present the results in Table IA.6 in the Internet Appendix. During both subperiods, we find that institutions tend to trade in the right (wrong) direction of the underreaction (overreaction) anomalies.

4.4.3. *Year-by-year results*

To investigate whether our findings vary over time, we repeat our analysis year-by-year and plot the results in Fig. 1. Panel A shows the results for the first measure of institutional trading, while Panel B shows the results for the second measure. In each panel, the blue line shows the net institutional trading for underreaction anomalies, while the red line shows the net institutional trading for overreaction anomalies. Overall, our finding that institutions tend to trade in the right direction of the underreaction anomalies and wrong direction of overreaction anomalies is fairly robust across years. Specifically, the net institutional trading for overreaction anomalies is negative every year in our sample period. The net institutional trading is highly positive for underreaction anomalies for most years in

[15] We acknowledge that the total short interest is a noisy proxy for the short positions by hedge funds.
[16] This finding is somewhat different from that of Calluzzo et al. (2019), who show that some institutions trade on anomalies after they are published. We note that our sample period and anomaly sample are different from theirs. More importantly, we follow Edelen et al. (2016) and examine institutional trading during the anomaly formation period, whereas Calluzzo et al. (2019) focus primarily on the post-formation period.

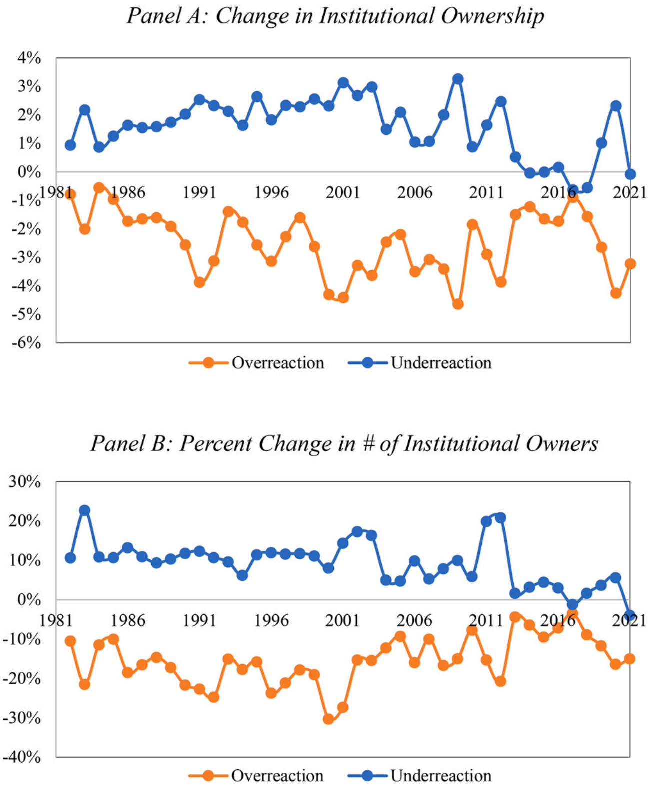

Fig. 1. Institutional trading on accounting anomalies – year-by-year results This figure plots the year-by-year net institutional trading in anomaly long-short portfolios during the anomaly formation period across 56 accounting anomalies. The list and definitions of the anomalies are contained in Appendix A. The formation period is the six quarters preceding the anomaly formation date. We use a K-means clustering model to classify our sample anomalies into two categories, overreaction anomalies and underreaction anomalies. Change in institutional ownership is the change in percentage of shares held by institutions. Percent change in the number of institutional owners is the change in the logarithm of the number of institutional owners. The net institutional trading is the difference in institutional trading between the long-leg stocks and the short-leg stocks. Our sample period is from 1982 to 2021.

our sample period except a few years toward the end of our sample period.

4.5. *Instiutional trading and anomaly returns*

In this section, we examine the relation between institutional trading and subsequent anomaly returns. Specifically, we compute anomaly long-short returns separately among stocks for which institutions trade in the right or wrong direction of anomalies. This analysis also helps us answer the question whether institutional trading is stabilizing or destabilizing. For example, if overreaction anomalies are aggravated by institutions' tendency to trade in the wrong direction, then institutional trading would be destabilizing. By the same token, if underreaction anomalies are alleviated by institutions' tendency to trade in the right direction, then institutional trading would be stabilizing.

We construct two conditional long-short portfolios. The first is *long_buy_short_sell*, which takes long positions in the long-leg stocks that institutions bought during the formation period and takes short positions in the short-leg stocks that institutions sold during the formation period. We track the performance of this portfolio during the anomaly's holding period. The second portfolio is *long_sell_short_buy*, which takes long positions in the long-leg stocks that institutions sold during the formation period and takes short positions in the short-leg stocks that institutions bought. Essentially, *long_buy_short_sell* gives us the long-short return among stocks where institutions trade in the right direction of the anomalies, while *long_sell_short_buy* gives us the long-short return among stocks where institutions trade in the opposite direction of the anomalies. In addition to raw returns, we also estimate CAPM alpha, Fama and French (1996) 3-factor alpha, and Carhart (1997) 4-factor alpha of long-short returns.

Panel A of Table 6 presents the results for overreaction anomalies. The average *long_buy_short_sell* is 0.00% per month, while the average *long_sell_short_buy* is 0.66% per month. The difference between the two is −0.66% per month (t-stat = −3.33). The 1-, 3-, and 4-factor alphas are qualitatively similar. These results indicate that an anomaly's subsequent long-short returns are significantly higher when institutions trade in the wrong direction of the anomaly during the formation period. In fact, when institutions are trading in the right direction, subsequent long-short anomaly returns are statistically indistinguishable from zero. Given that institutions tend to trade in the wrong direction of overreaction anomalies, our results are consistent with institutional trading aggravating overreaction

Table 6
Anomaly returns conditional on direction of institutional trading.

Panel A: Overreaction anomalies						
	long_buy_short_sell	*t*-stat	*long_sell_short_buy*	*t*-stat	Diff	*t*-stat
Raw return	0.00%	−0.04	0.66%	4.24	−0.66%	−3.33
1-factor alpha	0.08%	0.93	0.66%	4.41	−0.58%	−3.22
3-factor alpha	0.02%	0.31	0.57%	4.61	−0.55%	−3.34
4-factor alpha	−0.06%	−0.83	0.62%	4.81	−0.68%	−4.13
Panel B: Underreaction anomalies						
	long_buy_short_sell	*t*-stat	*long_sell_short_buy*	*t*-stat	Diff	*t*-stat
Raw return	−0.12%	−0.69	0.57%	7.79	−0.69%	−3.50
1-factor alpha	−0.01%	−0.03	0.61%	8.22	−0.62%	−3.43
3-factor alpha	0.02%	0.11	0.58%	8.81	−0.57%	−3.49
4-factor alpha	−0.14%	−1.01	0.54%	8.07	−0.68%	−4.21

This table reports results for monthly anomaly returns conditional on formation period institutional trading. The list and definitions of the 56 accounting anomalies are contained in Appendix A. We obtain monthly stock data from the CRSP and accounting data from Compustat. Quarterly institutional holdings are from Thomson/Refinitiv 13F data. Our sample consists of NYSE, AMEX, and NASDAQ common stocks (with a CRSP share code of 10 or 11). We exclude financial stocks. We sort all sample stocks into terciles based on each anomaly variable and construct equal-weighted portfolios. Stocks in the long (short) portfolio are expected to outperform (underperform) according to prior literature. The formation period is the six quarters preceding the anomaly formation date. We use a K-means clustering model to classify our sample anomalies into two categories, overreaction anomalies and underreaction anomalies. Change in institutional ownership is the change in percentage of shares held by institutions. For each anomaly, we construct two portfolios. The *long_buy_short_sell* portfolio takes long positions in the stocks in the anomaly long leg that institutions bought during the formation period, and short positions in the stocks in the anomaly short leg that institutions sold during the formation period. The *long_sell_short_buy* portfolio takes long positions in the stocks in the anomaly long leg that institutions sold during the formation period, and short positions in the stocks in the anomaly short leg that institutions bought during the formation period. The *t*-statistic for the difference between the *long_buy_short_sell* and the *long_sell_short_buy* portfolios is calculated using the Newey-West standard errors. We obtain Fama and French (1996) three factors and the momentum factor from Kenneth French's website. Our sample period is from 1982 to 2021.

anomalies.

Panel B presents the results for underreaction anomalies. We find similar results to those in Panel A. The average *long_buy_short_sell* is −0.12% per month, while the average *long_sell_short_buy* is 0.57% per month. The difference between the two is −0.69% per month (*t*-stat = −3.50). We again find that an anomaly's subsequent long-short returns are significantly higher when institutions trade in the wrong direction of the anomaly during the formation period. However, the interpretation of the result is different than that in Panel A. Because institutions tend to trade in the right direction of underreaction anomalies and such trading leads to significantly lower anomaly returns, our results are consistent with institutional trading mitigating mispricing by speeding up the price adjustment process for underreaction anomalies.

Overall, we find that anomalies tend to exhibit significantly higher subsequent long-short returns when institutions trade in the wrong direction of the anomaly during the formation period. This finding is consistent with Edelen et al. (2016). However, our interpretation is somewhat different from theirs. While Edelen et al. (2016) interpret the results as suggesting that institutions aggravate market anomalies, we note that this interpretation only applies to overreaction anomalies. For underreaction anomalies, institutions' tendency to trade in the right direction appears to mitigate market mispricing and reduce subsequent long-short returns. We acknowledge that both institutional trading and anomaly returns are potentially influenced by many factors, and that our evidence by itself does not establish a causal relationship between institutional trading and anomaly returns.

4.6. Why do institutions trade in the direction of news?

As discussed in Section 2.2., there are several potential explanations for why institutions tend to trade in the direction of news. We provided evidence on these explanations in this section.

4.6.1. Prudent-man law

If institutions' trading in the direction of news is motivated by the prudent-man law, and to the extent that the prudent man law is more relevant for banks and insurance companies (Badrinath et al. (1989) and Chen et al. (2007)), we would expect our finding to be stronger for banks and insurance companies than for investment companies and independent money managers. To test this hypothesis, we classify all institutions into five groups by legal type, namely banks, insurance companies, investment companies, independent investment advisors, and others.[17] We then repeat our analysis in Panel A of Tables 2 and 3 separately for each legal type.

We report the results in Table 7, with the two panels corresponding to the two news measures, i.e., SUE and TRNA news. Across both panels, we find little evidence that banks and insurance companies exhibit a stronger tendency to trade in the direction of news than investment managers and investment advisors, which is inconsistent with the prudent-man law hypothesis.

[17] We obtain the 13F institutions' legal types from Brian Bushee's website, https://accounting-faculty.wharton. upenn.edu/bushee/.

Table 7
Institutional trading and news by institutional investor legal types.

Panel A: SUE				
	Change in institutional ownership			
	SUE > 0	*SUE* < 0	Difference	*t*-stat
Banks	0.09%	−0.05%	0.13%	8.09
Insurance companies	0.08%	−0.07%	0.15%	5.13
Investment managers	0.02%	−0.02%	0.04%	4.95
Investment advisors	0.01%	−0.07%	0.08%	7.10
Others	0.02%	0.00%	0.02%	6.04
	Percentage change in # of institutional owners			
	SUE > 0	*SUE* < 0	Difference	*t*-stat
Banks	2.56%	−0.18%	2.74%	11.41
Insurance companies	4.11%	0.13%	3.98%	11.59
Investment managers	2.42%	−0.53%	2.95%	11.29
Investment advisors	1.57%	−1.18%	2.74%	9.65
Others	3.32%	0.20%	3.12%	12.46
Panel B: NetNews				
	Change in institutional ownership			
	NetNews > 0	*NetNews* < 0	Difference	*t*-stat
Banks	0.04%	−0.02%	0.06%	4.65
Insurance companies	0.28%	0.11%	0.17%	3.10
Investment managers	0.00%	−0.04%	0.04%	6.33
Investment advisors	0.05%	−0.03%	0.08%	3.43
Others	0.00%	0.00%	−0.01%	−1.91
	Percentage change in # of institutional owners			
	NetNews > 0	*NetNews* < 0	Difference	*t*-stat
Banks	2.02%	0.21%	1.81%	7.61
Insurance companies	3.30%	0.52%	2.78%	11.76
Investment managers	1.73%	−0.34%	2.06%	8.61
Investment advisors	0.30%	−1.93%	2.23%	11.66
Others	2.34%	0.35%	1.99%	9.58

This table examines the relation between news and institutional trading by institutional investor legal types (banks, insurance companies, investment companies, independent investment advisors, and others). Quarterly institutional holdings are from Thomson/Refinitiv 13F data. We obtain the legal types of 13F institutions from Brian Bushee's website, https://accounting-faculty.wharton.upenn.edu/bushee/. SUE is the difference between current-quarter earnings per share (EPS) and the EPS four quarters ago, scaled by the standard deviation of unexpected earnings during the past eight quarters. We obtain a comprehensive sample of newswire releases from Thomson Reuters News Analytics (TRNA). We select the news items with a relevance score of 1 to ensure that the related firm is the focus of the news. We match the firms in TRNA with the stocks in CRSP through tickers. For each stock, we count the total number of news articles and the total number of news articles with positive and negative sentiment in a given quarter. *NetNews* is defined as the total number of good news minus the total number of bad news and then scaled by the total number of news. Change in institutional ownership is the change in percentage of shares held by institutions. Percent change in the number of institutional owners is the change in the logarithm of the number of institutional owners.

We also examine whether our main result, i.e., institutions trade in the right direction of underreaction anomalies and wrong direction of overreaction anomalies, is stronger for banks and insurance companies. We find no such evidence. For brevity, we report the results in Table IA.7 in the Internet Appendix.

4.6.2. Agency problems and short-termism

We follow Bushee (1998, 2001) and classify institutions as dedicated, transient, and quasi-indexers according to an institution's investment horizon and portfolio concentration. According to the agency and short-termism explanation, we should expect our finding to be stronger for transient institutions than for dedicated investors.[18]

In Table 8, we examine whether transient investors exhibit a stronger tendency to trade in the direction of news. The results indicate that while transient investors consistently trade in the same direction as the sentiment of news, dedicated investors frequently trade in the opposite direction of news. The opposite trading behavior by dedicated investors is likely due to the fact that they have large position sizes and long investment horizons, and are less influenced by the agency problems in the money management industry.

In Table IA.8 in the Internet Appendix, we show that our main finding, i.e., institutions trade in the right direction of underreaction anomalies and wrong direction of overreaction anomalies, is qualitatively and quantitatively stronger for transient institutions than for long-term, dedicated investors. This result supports the agency problem and short-termism hypothesis.

[18] Previous studies have also shown that short-term institutions are better informed. Ke and Ramalingegowda (2005), for example, document that institutions with high portfolio turnover, i.e., transient institutions, are active in exploiting the post-earnings announcement drift anomaly. Similarly, Yan and Zhang (2009) show that trading by short-term institutions has greater predictive power for future returns than long-term institutions.

Table 8
Institutional trading and news by transient investors, quasi-indexers, and dedicated investors.

Panel A: SUE				
	Change in institutional ownership			
	SUE > 0	*SUE* < 0	Difference	*t*-stat
Transient investors	0.06%	−0.07%	0.13%	6.65
Quasi-indexers	0.17%	−0.16%	0.33%	9.01
Dedicated investors	−0.01%	0.02%	−0.03%	−3.73
	Percentage change in # of institutional owners			
	SUE > 0	*SUE* < 0	Difference	*t*-stat
Transient investors	4.06%	−0.64%	4.69%	8.44
Quasi-indexers	3.44%	0.20%	3.24%	13.65
Dedicated investors	0.39%	−0.65%	1.05%	3.27
Panel B: NetNews				
	Change in institutional ownership			
	NetNews > 0	*NetNews* < 0	Difference	*t*-stat
Transient investors	0.13%	−0.07%	0.20%	4.81
Quasi-indexers	0.29%	0.09%	0.20%	4.22
Dedicated investors	−0.03%	0.03%	−0.06%	−3.57
	Percentage change in # of institutional owners			
	NetNews > 0	*NetNews* < 0	Difference	*t*-stat
Transient investors	3.11%	−0.26%	3.37%	10.81
Quasi-indexers	2.75%	0.64%	2.11%	10.70
Dedicated investors	−0.10%	−0.23%	0.13%	0.66

This table examines the relation between earnings news and institutional trading for subsets of institutions classified based on investment horizon and position size. We follow Bushee (1998, 2001) and classify institutions as dedicated, transient, and quasi-indexers. We obtain institutional investor classifications from Brian Bushee's website https://accounting-faculty.wharton.upenn.edu/bushee/. SUE is the difference between current-quarter earnings per share (EPS) and the EPS four quarters ago, scaled by the standard deviation of unexpected earnings during the past eight quarters. We obtain a comprehensive sample of newswire releases from Thomson Reuters News Analytics (TRNA). We select the news items with a relevance score of 1 to ensure that the related firm is the focus of the news. We match the firms in TRNA with the stocks in CRSP through tickers. For each stock, we count the total number of news articles and the total number of news articles with positive and negative sentiment in a given quarter. *NetNews* is defined as the total number of good news minus the total number of bad news and then scaled by the total number of news. Change in institutional ownership is the change in percentage of shares held by institutions. Percent change in the number of institutional owners is the change in the logarithm of the number of institutional owners.

4.6.3. Window dressing

Window dressing by institutional investors refers to the practice of making changes to a portfolio's holdings near the end of a reporting period, such as a quarter or a year, with the primary goal of improving the appearance of the portfolio's performance. Institutional investors may engage in window dressing to make their portfolio holdings appear more attractive to current and potential clients. Common tactics used in window dressing include buying high-performing stocks or assets shortly before the reporting period to show that the portfolio holds winners as well as selling underperforming or losing positions to minimize their visibility in the portfolio report. It's important to note that while window dressing can enhance the appearance of a portfolio's performance in the short term, it doesn't reflect the true investment strategy or long-term performance of the fund.

To test whether window dressing is the motivation behind institutional trading in the direction of news, we obtain a transaction-level institutional trading database, namely the ANcerno database for the sample period 2003–2013.[19] We aggregate the transactions of institutions for each stock to a daily frequency. We test two predictions of the window dressing hypothesis. First, institutional buying of good news stocks and selling of bad news stocks should be concentrated at the end of the quarter. Second, the above trading behavior should be more pronounced at year-ends than quarter-ends. Overall, we find little support for either of the above predictions. For brevity, we present our results in Table IA.9-10 in the Internet Appendix.

4.6.4. Market underreaction and over-extrapolation

Institutions may trade in the direction of news if they believe that the market underreacts to news. Alternatively, if institutional investors over-extrapolate past performance, they will also trade in the direction of news. To differentiate between these two explanations, we examine institutional trading during and after earnings announcements. Previous studies (e.g., Bernard and Thomas (1989, 1990)) have shown that price drifts in the direction of earnings news for about 60 trading days after the earnings announcement. Thus, if institutions' buying stocks with positive earnings news and selling stocks with negative earnings news are motivated by market underreaction, we should observe this trading behavior during the earnings announcement quarter and possibly during the subsequent quarter. On the other hand, if institutions over-extrapolate past earnings news too far into the future, we would observe this trading behavior long after the earnings announcement quarter.

[19] For more details about the ANcerno database, please see Puckett and Yan (2011).

In our empirical test, we study institutional trading behavior during the quarter of the earnings announcement (Q+0) as well as eight quarters (Q+1 to Q+8) subsequent to the earnings announcement quarter. For brevity, we present the results in Table IA.11 in the Internet Appendix. Overall, we find that the net institutional trading is significantly positive not only during Q+0 and Q+1, but also during Q+2 through Q+4. The positive net institutional trading during Q+0 and Q+1 is consistent with institutional trading on the market underreaction to earnings news. The positive net institutional trading during Q+2 and Q+4, however, is consistent with institutions extrapolating past news too far into the future.

5. Conclusions

We examine how institutional investors trade with respect to accounting anomalies. We classify anomalies as underreaction or overreaction anomalies based on a clustering analysis. We find that institutional investors, as a group, trade in the wrong direction of overreaction anomalies, but in the right direction of underreaction anomalies. The heterogenous institutional trading patterns across underreaction and overreaction anomalies do not necessarily reflect institutions' differential anomaly trading skills; rather, they can be simply explained by institutions' tendency to trade in the direction of news, i.e., buying on good news and selling on bad news. We find strong support for this explanation by examining institutional trading around earnings news and a comprehensive database of newswire releases. We explore why institutions tend to trade in the direction of news, and find supporting evidence for the agency problem and short-termism, market underreaction, and overextrapolation hypotheses. We find no evidence for the prudent-man law and window dressing hypotheses. Our results hold for both mutual funds and hedge funds. Examination of short positions, i.e., total short interest, indicates that short sellers trade in the right direction of both underreaction and overreaction anomalies. Finally, institutional trading appears to exacerbate market mispricing associated with overreaction anomalies, while mitigating mispricing associated with underreaction anomalies.

Appendix A

List of Accounting Anomalies

Our sample of 56 accounting anomalies is compiled from Green et al. (2013), Hou et al. (2015), and McLean and Pontiff (2016). We restrict our sample to anomaly variables that are continuous (rather than indicator variables) and can be constructed primarily using the CRSP and/or COMPUSTAT data. We exclude anomalies related to liquidity or trading frictions. We use a K-means clustering model to classify our sample anomalies into two categories, overreaction anomalies and underreaction anomalies.

Panel A: Overreaction Anomalies		
Abbreviation	Anomaly	Authors
A/ME	Market leverage	Bhandari (1988)
ACI	Abnormal corporate investment	Titman et al. (2004)
AD/M	Advertisement expense-to-market	Chan et al. (2001)
B/M	Book-to-market equity	Rosenberg et al. (1985)
B/P-E	Enterprise component of book-to-price	Penman et al. (2007)
BeG	Growth in book equity	Lockwood and Prombutr (2010)
CF/P	Cash flow-to-price	Lakonishok et al. (1994)
D/P	Dividend yield	Litzenberger et al., (1979)
Dur	Equity duration	Dechow et al. (2004)
E/P	Earnings-to-price	Basu (1983)
E_con	Earnings consistency	Alwathainani (2009)
Enter	Enterprise multiple	Loughran and Wellman (2012)
H/N	Hiring rate	Belo et al. (2014)
AG	Asset growth	Cooper et al. (2008)
I-ADJ	Industry-adjusted growth in investment	Abarbanell and Bushee (1998)
IG	Investment growth	Xing (2008)
IvC	Inventory changes	Thomas and Zhang (2002)
IvG	Inventory growth	Belo and Lin (2012)
NoaG	Growth in net operating assets minus accruals	Fairfield et al. (2003)
O/P	Payout yield	Boudoukh et al. (2007)
OA	Operating accruals	Sloan (1996)
PI/A	Changes in PP&E plus changes in inventory	Lyandres et al. (2008)
POA	Percent operating accruals	Hafzalla et al. (2011)
PTA	Percent total accruals	Hafzalla et al. (2011)
RD/M	R&D-to-market	Chan et al. (2001)
S/P	Sales-to-price	Barbee et al. (1996)
SG	Sales growth	Lakonishok et al. (1994)
TA	Total accruals	Richardson et al. (2005)

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Panel A: Overreaction Anomalies		
Abbreviation	Anomaly	Authors
Z	*Z*-score	Dichev (1998)
Panel B: Underreaction Anomalies		
Abr-1	Abnormal returns around earnings announcements	Chan et al. (1996)
ATO	Asset turnover	Soliman (2008)
B/P-Lev	Leverage component of book-to-price	Penman et al. (2007)
CTO	Capital turnover	Haugen and Baker (1996)
D_ATO	Change in asset turnover	Soliman (2008)
D_PM	Change in profit margin	Soliman (2008)
Exclexp	Excluded Expenses	Doyle et al. (2003)
F	*F* -score	Piotroski (2000)
FP	Failure probability	Campbell et al. (2008)
GP/A	Gross profitability-to-assets	Novy-Marx (2013)
NO/P	Net payout yield	Boudoukh et al. (2007)
NOA	Net operating assets	Hirshleifer et al. (2004)
NXF	Net external financing	Bradshaw et al. (2006)
O	*O*-score	Dichev (1998)
OL	Operating leverage	Novy-Marx (2011)
PM	Profit margin	Soliman (2008)
Pension	Pension funding status	Franzoni and Marin (2006)
RD/S	R&D-to-sales	Chan et al. (2001)
RNA	Return on net operating assets	Soliman (2008)
ROA	Return on assets	Balakrishnan et al. (2010)
ROE	Return on equity	Haugen and Baker (1996)
RS	Revenue surprise	Jegadeesh and Livnat (2006)
S/IV	Change in sales minus change in inventory	Abarbanell and Bushee (1998)
S/SGA	Change in sales minus change in SG&A	Abarbanell and Bushee (1998)
SUE	Earnings surprise	Foster et al. (1984)
TES	Tax expense surprise	Thomas and Zhang (2011)
TI/BI	Taxable income-to-book income	Lev and Nissim (2004)

Internet Appendix

Table IA.1
Correlations of long-short returns and institutional trading across accounting anomalies

Panel A: Correlations of Formation Period Return						
	mean	p10	p25	p50	p75	p90
	EW					
Overreaction Anomalies	0.38	0.04	0.19	0.38	0.60	0.76
Underreaction Anomalies	0.24	−0.25	0.00	0.28	0.51	0.73
	VW					
Overreaction Anomalies	0.29	−0.01	0.16	0.29	0.42	0.57
Underreaction Anomalies	0.21	−0.08	0.05	0.20	0.38	0.56
Panel B: Correlations of Holding Period Return						
	mean	p10	p25	p50	p75	p90
	EW					
Overreaction Anomalies	0.29	−0.10	0.08	0.30	0.53	0.69
Underreaction Anomalies	0.23	−0.19	0.03	0.22	0.47	0.75
	VW					
Overreaction Anomalies	0.25	−0.03	0.11	0.25	0.38	0.51
Underreaction Anomalies	0.16	−0.10	0.01	0.13	0.30	0.56
Panel C: Correlations of Institutional Trading						
	mean	p10	p25	p50	p75	p90
	Change in institutional ownership					
Overreaction Anomalies	0.44	0.08	0.29	0.46	0.64	0.77
Underreaction Anomalies	0.26	−0.29	0.01	0.33	0.55	0.74
	Percent Change in the number of institutional owners					
Overreaction Anomalies	0.46	0.06	0.29	0.49	0.68	0.78
Underreaction Anomalies	0.29	−0.42	0.07	0.40	0.61	0.80

This table reports the distributions of correlations of long-short returns and correlations of institutional trading among underreaction anomalies and among overreaction anomalies. We obtain monthly stock data from the CRSP, accounting data from Compustat. Quarterly institutional holdings are from Thomson/Refinitiv 13F data. Our sample consists of NYSE, AMEX, and NASDAQ common stocks (with a CRSP share code of 10 or 11). We exclude financial stocks. We sort all sample stocks into terciles based on each anomaly variable. We use a K-means clustering model to classify our sample anomalies into two categories, overreaction anomalies and underreaction anomalies. Change in institutional ownership is the change in percentage of shares held by institutions, measured over the 6 quarters prior to portfolio formation date. Percent change in the number of institutional owners is the change in the logarithm of the number of institutional owners over the 6 quarters prior to portfolio formation date. Our sample period is from 1982 to 2021.

Table IA.2
Institutional trading on accounting anomalies during the anomaly formation period – Anomaly-by-Anomaly Results

Panel A: Change in Institutional Ownership				
Panel A1: Overreaction anomalies				
Anomaly	Long	Short	Long - Short	*t*-stat
A/ME	0.17%	4.52%	−4.34%	−7.45
ACI	1.89%	2.21%	−0.32%	−3.00
AD/M	0.47%	3.54%	−3.08%	−8.09
B/M	0.10%	4.05%	−3.95%	−7.73
B/P-E	0.11%	4.07%	−3.97%	−8.05
BeG	0.02%	4.69%	−4.67%	−10.62
CF/P	1.41%	4.06%	−2.65%	−7.15
D/P	1.38%	3.03%	−1.65%	−6.13
Dur	1.72%	2.87%	−1.14%	−4.00
E/P	1.88%	3.79%	−1.91%	−5.55
E_con	0.56%	3.83%	−3.27%	−8.50
Enter	1.62%	3.59%	−1.97%	−5.07
H/N	0.58%	4.07%	−3.50%	−9.24
I-ADJ	1.19%	2.41%	−1.22%	−8.11
AG	0.26%	4.39%	−4.12%	−8.19
IG	1.31%	3.23%	−1.92%	−9.92
IvC	1.21%	2.79%	−1.59%	−7.54
IvG	1.22%	2.94%	−1.72%	−7.88
NoaG	1.38%	3.00%	−1.62%	−6.16
O/P	1.00%	3.01%	−2.01%	−10.77
OA	1.60%	2.83%	−1.23%	−6.66
PI/A	1.26%	3.16%	−1.90%	−6.17
POA	1.97%	2.85%	−0.88%	−5.38
PTA	0.72%	3.69%	−2.96%	−9.55
RD/M	0.15%	3.63%	−3.48%	−5.49
S/P	0.46%	3.83%	−3.37%	−6.45
SG	1.30%	2.12%	−0.81%	−4.18
TA	0.71%	3.96%	−3.25%	−8.75
Z	0.71%	3.77%	−3.05%	−7.33
Panel A2: Underreaction anomalies				
Anomaly	Long	Short	Long - Short	*t*-stat
ATO	2.94%	1.45%	1.49%	9.52
Abr-1	2.94%	2.12%	0.81%	4.49
B/P-Lev	3.08%	0.22%	2.85%	6.44
CTO	3.02%	1.54%	1.48%	6.69
D_ATO	2.97%	1.55%	1.42%	6.47
D_PM	3.47%	0.67%	2.80%	7.68
Exclexp	3.32%	2.82%	0.50%	1.40
F	3.51%	0.87%	2.64%	5.60
FP	4.22%	−0.59%	4.80%	6.67
GP/A	2.66%	1.91%	0.75%	2.79
NO/P	1.35%	3.20%	−1.85%	−5.02
NOA	1.96%	2.90%	−0.94%	−2.63
NXF	1.75%	3.17%	−1.42%	−4.72
O	3.29%	0.78%	2.51%	4.68
OL	1.78%	2.64%	−0.86%	−3.28
PM	3.45%	0.72%	2.73%	5.06
Pension	2.92%	0.95%	1.97%	5.44
RD/S	2.07%	2.17%	−0.10%	−0.30
RNA	3.81%	0.41%	3.40%	7.27
ROA	4.26%	0.85%	3.41%	4.28
ROE	4.22%	0.93%	3.29%	4.02
RS	3.84%	1.13%	2.71%	8.27
S/IV	2.50%	1.96%	0.54%	8.74
S/SGA	3.27%	1.01%	2.26%	7.38
SUE	3.53%	1.42%	2.11%	3.00
TES	3.85%	1.56%	2.29%	3.39
TI/BI	2.86%	1.66%	1.19%	2.21

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Table IA.2 (*continued*)

Panel B: Percent Change in # of Institutional Owners				
Panel B1: Overreaction anomalies				
Anomaly	Long	Short	Long - Short	*t*-stat
A/ME	2.59%	28.27%	−25.68%	−8.21
ACI	12.30%	13.53%	−1.22%	−1.27
AD/M	4.41%	21.33%	−16.91%	−6.06
B/M	1.33%	27.12%	−25.79%	−8.99
B/P-E	1.77%	26.39%	−24.62%	−8.18
BeG	0.98%	30.12%	−29.14%	−11.30
CF/P	9.13%	22.85%	−13.72%	−6.34
D/P	6.52%	19.91%	−13.39%	−7.38
Dur	9.27%	20.82%	−11.55%	−7.03
E/P	12.25%	21.48%	−9.24%	−4.78
E_con	2.44%	26.65%	−24.21%	−9.15
Enter	10.28%	20.59%	−10.31%	−4.94
H/N	3.33%	25.99%	−22.66%	−14.10
I-ADJ	8.22%	16.80%	−8.58%	−6.60
AG	2.55%	28.00%	−25.46%	−12.15
IG	8.92%	20.94%	−12.02%	−8.22
IvC	7.66%	18.56%	−10.90%	−8.55
IvG	7.57%	18.97%	−11.40%	−7.53
NoaG	9.67%	19.60%	−9.93%	−5.14
O/P	5.41%	18.92%	−13.52%	−8.14
OA	11.49%	18.15%	−6.66%	−3.83
PI/A	7.67%	21.00%	−13.33%	−6.27
POA	10.78%	19.21%	−8.43%	−4.35
PTA	5.56%	21.60%	−16.04%	−9.18
RD/M	1.21%	23.31%	−22.10%	−6.15
S/P	4.94%	23.97%	−19.03%	−5.72
SG	9.18%	12.85%	−3.67%	−3.54
TA	6.58%	24.10%	−17.52%	−6.92
Z	5.58%	22.98%	−17.40%	−8.17
Panel B2: Underreaction anomalies				
Anomaly	Long	Short	Long - Short	*t*-stat
ATO	19.49%	9.17%	10.31%	5.66
Abr-1	18.38%	13.44%	4.93%	8.37
B/P-Lev	20.57%	3.47%	17.09%	7.30
CTO	20.45%	9.54%	10.91%	4.67
D_ATO	20.49%	8.56%	11.94%	9.94
D_PM	23.91%	3.09%	20.82%	14.69
Exclexp	15.65%	13.50%	2.15%	2.48
F	21.74%	7.21%	14.53%	7.09
FP	23.63%	2.17%	21.45%	7.12
GP/A	17.10%	12.86%	4.24%	2.12
NO/P	6.83%	20.31%	−13.48%	−6.57
NOA	11.86%	20.02%	−8.16%	−3.09
NXF	11.11%	20.68%	−9.57%	−5.12
O	17.97%	9.73%	8.23%	3.49
OL	13.93%	15.80%	−1.87%	−0.98
PM	19.99%	7.16%	12.83%	4.72
Pension	16.51%	5.29%	11.22%	6.80
RD/S	12.80%	13.19%	−0.39%	−0.13
RNA	23.27%	5.51%	17.77%	5.95
ROA	26.47%	7.01%	19.46%	4.80
ROE	26.96%	6.95%	20.01%	4.93
RS	23.26%	6.28%	16.98%	12.66
S/IV	17.00%	10.97%	6.03%	8.99
S/SGA	21.64%	6.43%	15.22%	14.69
SUE	23.46%	6.91%	16.56%	7.20
TES	22.77%	6.14%	16.62%	5.40
TI/BI	16.55%	13.19%	3.35%	1.25

This table reports results for institutional trading during the anomaly portfolio formation period for all 56 accounting anomalies. We obtain monthly stock data from the CRSP, accounting data from Compustat. Quarterly institutional holdings are from Thomson/Refinitiv 13F data. Our sample consists of NYSE, AMEX, and NASDAQ common stocks (with a CRSP share code of 10 or 11). We exclude financial stocks. We sort all sample stocks into terciles based on each anomaly variable. We use a K-means clustering model to classify our sample anomalies into two categories, overreaction anomalies and underreaction anomalies. Change in institutional ownership is the change in percentage of shares held by institutions, measured over the past 6 quarters. Percent change in the number of institutional owners is the change in the logarithm of the number of institutional owners over the past 6 quarters. In June of each year we calculate the average institutional trading measures for the long and short leg of an anomaly portfolio, and the difference in institutional trading between the long and short leg. The *t*-statistics for the differences between the long and short legs are calculated using the Newey-West standard errors. Our sample period is from 1982 to 2021.

Table IA.3
Institutional trading and Earnings Surprise

Panel A: Institutional Trading and ES	ES > 0	ES < 0	Difference
Change in institutional ownership	0.71% (7.11)	0.14% (1.12)	0.57% (5.51)
Percentage change in # of institutional owners	3.61% (9.78)	0.37% (0.77)	3.23% (7.41)

Panel B: ES for Anomaly Portfolios	Long	Short	L-S	*t*-stat	# > 0	# ≫ 0	# < 0	# ≪ 0
Overreaction	−0.0015	−0.0004	−0.0011	−6.75	4	2	25	20
Underreaction	−0.0003	−0.0021	0.0018	6.48	22	22	4	2

This table examines the relation between earnings news and institutional trading in 55 accounting anomalies. The list and definitions of the anomalies are contained in Appendix A. We removed the PEAD anomaly to avoid confounding effect. We obtain monthly stock data from the CRSP and accounting data from Compustat. Quarterly institutional holdings are from Thomson/Refinitiv 13F data. Our sample consists of NYSE, AMEX, and NASDAQ common stocks (with a CRSP share code of 10 or 11). We exclude financial stocks. We sort all sample stocks into terciles based on each anomaly variable. Stocks in the long (short) portfolio are expected to outperform (underperform) according to prior literature. ES is the earnings surprise, defined as the difference between current-quarter earnings per share (EPS) and analyst earnings forecasts, scaled by the stock price. The formation period is the six quarters preceding the anomaly formation date. We use a K-means clustering model to classify our sample anomalies into two categories, overreaction anomalies and underreaction anomalies. Change in institutional ownership is the change in percentage of shares held by institutions. Percent change in the number of institutional owners is the change in the logarithm of the number of institutional owners. The *t*-statistics for the differences between the long and short legs are calculated using the Newey-West standard errors. "#>0", "#≫0", "#<0", and "#≪0" denote the number of anomalies where the long-short difference in institutional trading is positive, positive and significant at the 5% level, negative, and negative and significant at the 5% level, respectively. Our sample period is from 1984 to 2021.

Table IA.4
Institutional trading on accounting anomalies during the anomaly holding period

Panel A: Two Quarters	Long	Short	L-S	*t*-stat	# > 0	# ≫ 0	# < 0	# ≪ 0
	Change in Institutional Ownership							
Overreaction	0.36%	0.41%	−0.05%	−1.02	14	4	15	7
Underreaction	0.53%	0.32%	0.21%	4.55	24	13	3	0
	Percent Change in # of Institutional Owners							
Overreaction	2.56%	3.41%	−0.85%	−3.18	3	1	26	11
Underreaction	3.89%	2.21%	1.68%	4.55	25	17	2	0
Panel B: Four Quarters								
	Long	Short	L-S	*t*-stat	# > 0	# ≫ 0	# < 0	# ≪ 0
	Change in Institutional Ownership							
Overreaction	0.98%	1.10%	−0.12%	−1.36	9	0	20	6
Underreaction	1.28%	0.93%	0.35%	3.75	25	14	2	0
	Percent Change in # of Institutional Owners							
Overreaction	7.08%	7.87%	−0.79%	−1.77	6	0	23	4
Underreaction	8.51%	6.67%	1.84%	3.06	22	12	5	1

This table reports institutional trading in anomaly portfolios during the holding period across 56 accounting anomalies. The list and definitions of the anomalies are contained in Appendix A of the paper. We obtain monthly stock data from the CRSP and accounting data from Compustat. Quarterly institutional holdings are from Thomson/Refinitiv 13F data. Our sample consists of NYSE, AMEX, and NASDAQ common stocks (with a CRSP share code of 10 or 11). We exclude financial stocks. We sort all sample stocks into terciles based on each anomaly variable. Stocks in the long (short) portfolio are expected to outperform (underperform) according to prior literature. The holding period is two or four quarters subsequent to the anomaly formation date. We use a K-means clustering model to classify our sample anomalies into two categories, overreaction anomalies and underreaction anomalies. Change in institutional ownership is the change in percentage of shares held by institutions. Percent change in the number of institutional owners is the change in the logarithm of the number of institutional owners. The anomaly formation date is June 30 of each year. The *t*-statistics for the differences between the long and short legs are calculated using the Newey-West standard errors. "#>0", "#≫0", "#<0", and "#≪0" denote the number of anomalies where the long-short difference in institutional trading is positive, positive and significant at the 5% level, negative, and negative and significant at the 5% level, respectively. Our sample period is from 1982 to 2021.

Table IA.5
Institutional trading on accounting anomalies – Pre- and Post-Publication Periods

Panel A: Change in Institutional Ownership	Long	Short	L-S	*t*-stat	# > 0	# ≫ 0	# < 0	# ≪ 0
	Pre-publication Period							
Overreaction	1.11%	3.66%	−2.56%	−7.27	0	0	24	23

(*continued on next page*)

Table IA.5 (*continued*)

	Long	Short	L-S	*t*-stat	# > 0	# ≫ 0	# < 0	# ≪ 0
Underreaction	3.38%	1.45%	1.93%	10.35	19	19	5	4
	Post-publication Period							
Overreaction	0.72%	3.50%	−2.78%	−9.97	0	0	24	24
Underreaction	2.84%	1.30%	1.55%	3.68	19	15	5	3
Panel B: Percent Change in # of Institutional Owners								
	Long	Short	L-S	*t*-stat	# > 0	# ≫ 0	# < 0	# ≪ 0
	Pre-publication Period							
Overreaction	6.65%	23.69%	−17.04%	−13.16	0	0	24	23
Underreaction	20.56%	9.58%	10.98%	16.82	20	18	4	3
	Post-publication Period							
Overreaction	3.87%	18.52%	−14.65%	−6.07	1	0	23	23
Underreaction	15.54%	7.24%	8.31%	4.26	19	15	5	3

This table reports institutional trading in anomaly portfolios before and after the publication year of the academic study that first documented each anomaly. The list and definitions of the 56 accounting anomalies are contained in Appendix A. We obtain monthly stock data from the CRSP and accounting data from Compustat. Quarterly institutional holdings are from Thomson/Refinitiv 13F data. Our sample consists of NYSE, AMEX, and NASDAQ common stocks (with a CRSP share code of 10 or 11). We exclude financial stocks. We sort all sample stocks into terciles based on each anomaly variable. Stocks in the long (short) portfolio are expected to outperform (underperform) according to prior literature. The formation period is the six quarters preceding the anomaly formation date. We use a K-means clustering model to classify our sample anomalies into two categories, overreaction anomalies and underreaction anomalies. Change in institutional ownership is the change in percentage of shares held by institutions. Percent change in the number of institutional owners is the change in the logarithm of the number of institutional owners. The anomaly formation date is June 30 of each year. The *t*-statistics for the differences between the long and short legs are calculated using the Newey-West standard errors. “#>0”, “#≫0”, “#<0”, and “#≪0” denote the number of anomalies where the long-short difference in institutional trading is positive, positive and significant at the 5% level, negative, and negative and significant at the 5% level, respectively. Our sample period is from 1982 to 2021.

Table IA.6
Institutional trading on accounting anomalies - Pre- and Post-2004 Periods

Panel A: Change in Institutional Ownership								
	Long	Short	L-S	*t*-stat	# > 0	# ≫ 0	# < 0	# ≪ 0
	Pre-2004 Period							
Overreaction	1.20%	3.56%	−2.36%	−6.18	0	0	29	28
Underreaction	3.46%	1.42%	2.04%	8.86	22	22	5	4
	Post-2004 Period							
Overreaction	0.71%	3.31%	−2.60%	−8.05	0	0	29	29
Underreaction	2.59%	1.56%	1.03%	2.71	22	15	5	3
Panel B: Percent Change in # of Institutional Owners								
	Long	Short	L-S	*t*-stat	# > 0	# ≫ 0	# < 0	# ≪ 0
	Pre-2004 Period							
Overreaction	7.72%	26.25%	−18.52%	−13.60	0	0	29	29
Underreaction	23.05%	11.08%	11.96%	15.60	23	21	4	3
	Post-2004 Period							
Overreaction	5.09%	16.50%	−11.42%	−9.75	1	0	28	27
Underreaction	14.23%	8.27%	5.97%	2.99	21	15	6	2

This table reports institutional trading in anomaly portfolios before and after 2004. The list and definitions of the 56 anomalies are contained in Appendix A. We obtain monthly stock data from the CRSP and accounting data from Compustat. Quarterly institutional holdings are from Thomson/Refinitiv 13F data. Our sample consists of NYSE, AMEX, and NASDAQ common stocks (with a CRSP share code of 10 or 11). We exclude financial stocks. We sort all sample stocks into terciles based on each anomaly variable. Stocks in the long (short) portfolio are expected to outperform (underperform) according to prior literature. The formation period is the six quarters preceding the anomaly formation date. We use a K-means clustering model to classify our sample anomalies into two categories, overreaction anomalies and underreaction anomalies. Change in institutional ownership is the change in percentage of shares held by institutions. Percent change in the number of institutional owners is the change in the logarithm of the number of institutional owners. The anomaly formation date is June 30 of each year. The *t*-statistics for the differences between the long and short legs are calculated using the Newey-West standard errors. “#>0”, “#≫0”, “#<0”, and “#≪0” denote the number of anomalies where the long-short difference in institutional trading is positive, positive and significant at the 5% level, negative, and negative and significant at the 5% level, respectively. Our sample period is from 1982 to 2021.

Table IA.7
Institutional trading on accounting anomalies by institutional investor legal types

Panel A: Change in Institutional Ownership								
	Long	Short	L-S	*t*-stat	# > 0	# ≫ 0	# < 0	# ≪ 0
	Banks							
Overreaction	0.10%	0.52%	−0.42%	−4.90	1	0	28	23
Underreaction	0.50%	0.14%	0.35%	3.61	23	19	4	0
	Insurance Companies							
Overreaction	0.00%	0.17%	−0.16%	−4.26	0	0	29	21

(continued on next page)

Table IA.7 (*continued*)

Panel A: Change in Institutional Ownership								
	Long	Short	L-S	*t*-stat	# > 0	# ≫ 0	# < 0	# ≪ 0
Underreaction	0.15%	0.03%	0.12%	3.42	22	18	5	2
	Investment companies							
Overreaction	−0.06%	0.40%	−0.46%	−4.24	0	0	29	27
Underreaction	0.32%	0.04%	0.28%	2.51	21	17	6	4
	Independent investment advisors							
Overreaction	0.28%	1.38%	−1.10%	−7.00	0	0	29	24
Underreaction	1.23%	0.51%	0.72%	2.52	23	15	4	2
	Others							
Overreaction	−0.02%	0.15%	−0.17%	−4.63	0	0	29	29
Underreaction	0.10%	0.05%	0.04%	2.12	17	12	10	4
Panel B: Percent Change in # of Institutional Owners								
	Long	Short	L-S	*t*-stat	# > 0	# ≫ 0	# < 0	# ≪ 0
	Banks							
Overreaction	5.36%	18.65%	−13.29%	−8.31	0	0	29	29
Underreaction	15.62%	8.74%	6.88%	6.71	23	19	4	3
	Insurance Companies							
Overreaction	2.56%	14.87%	−12.30%	−8.36	0	0	29	29
Underreaction	12.69%	4.63%	8.06%	7.97	22	21	5	3
	Investment companies							
Overreaction	1.51%	9.42%	−7.90%	−7.66	2	0	27	26
Underreaction	9.27%	0.85%	8.41%	5.44	22	22	5	4
	Independent investment advisors							
Overreaction	11.50%	24.98%	−13.47%	−7.72	1	0	28	27
Underreaction	23.98%	12.84%	11.14%	7.31	22	22	5	3
	Others							
Overreaction	4.50%	16.93%	−12.42%	−8.76	0	0	29	29
Underreaction	14.92%	6.53%	8.39%	8.22	22	21	5	4

This table reports institutional trading in anomaly portfolios by institutional investor legal types (banks, insurance companies, investment companies, independent investment advisors, and others) across 56 accounting anomalies. The list and definitions of the anomalies are contained in Appendix A. We obtain monthly stock data from the CRSP and accounting data from Compustat. Quarterly institutional holdings are from Thomson/Refinitiv 13F data. We obtain the legal types of 13F institutions from Brian Bushee's website, https://accounting-faculty.wharton.upenn.edu/bushee/. Our sample consists of NYSE, AMEX, and NASDAQ common stocks (with a CRSP share code of 10 or 11). We exclude financial stocks. We sort all sample stocks into terciles based on each anomaly variable. Stocks in the long (short) portfolio are expected to outperform (underperform) according to prior literature. The formation period is the six quarters preceding the anomaly formation date. We use a K-means clustering model to classify our sample anomalies into two categories, overreaction anomalies and underreaction anomalies. Change in institutional ownership is the change in percentage of shares held by institutions. Percent change in the number of institutional owners is the change in the logarithm of the number of institutional owners. The anomaly formation date is June 30 of each year. The *t*-statistics for the differences between the long and short legs are calculated using the Newey-West standard errors. "#>0", "#≫0", "#<0", and "#≪0" denote the number of anomalies where the long-short difference in institutional trading is positive, positive and significant at the 5% level, negative, and negative and significant at the 5% level, respectively. Our sample period is from 1982 to 2021.

Table IA.8
Institutional trading on accounting anomalies by transient investors, quasi-indexers, and dedicated investors

Panel A: Change in Institutional Ownership								
	Long	Short	L-S	*t*-stat	# > 0	# ≫ 0	# < 0	# ≪ 0
	Transient Investor							
Overreaction	−0.11%	0.18%	−0.29%	−2.54	10	8	19	13
Underreaction	0.37%	−0.26%	0.63%	3.41	23	15	4	1
	Quasi-indexer							
Overreaction	0.36%	2.41%	−2.05%	−6.09	0	0	29	27
Underreaction	1.92%	0.96%	0.96%	2.76	23	16	4	3
	Dedicated Investor							
Overreaction	0.05%	0.06%	−0.01%	−0.38	11	0	18	3
Underreaction	0.02%	0.09%	−0.07%	−2.37	9	0	18	10
Panel B: Percent Change in # of Institutional Owners								
	Long	Short	L-S	*t*-stat	# > 0	# ≫ 0	# < 0	# ≪ 0
	Transient Investor							
Overreaction	8.42%	18.98%	−10.56%	−6.86	2	1	27	24
Underreaction	19.98%	7.46%	12.52%	6.72	22	22	5	3
	Quasi-indexer							
Overreaction	8.92%	24.95%	−16.02%	−8.97	0	0	29	29
Underreaction	21.34%	12.92%	8.42%	7.14	23	20	4	3
	Dedicated Investor							

(continued on next page)

Table IA.8 (*continued*)

Panel A: Change in Institutional Ownership								
	Long	Short	L-S	*t*-stat	# > 0	# ≫ 0	# < 0	# ≪ 0
Overreaction	−1.26%	3.99%	−5.26%	−6.78	0	0	29	29
Underreaction	2.64%	0.19%	2.45%	2.30	23	14	4	3

This table reports institutional trading in anomaly portfolios by transient investors, quasi-indexers, and dedicated investors across 56 accounting anomalies. We obtain monthly stock data from the CRSP and accounting data from Compustat. Quarterly institutional holdings are from Thomson/Refinitiv 13F data. We obtain institutional investor classifications from Brian Bushee's website https://accounting-faculty.wharton.upenn.edu/bushee/. Our sample consists of NYSE, AMEX, and NASDAQ common stocks (with a CRSP share code of 10 or 11). We exclude financial stocks. We sort all sample stocks into terciles based on each anomaly variable. Stocks in the long (short) portfolio are expected to outperform (underperform) according to prior literature. The formation period is the six quarters preceding the anomaly formation date. We use a K-means clustering model to classify our sample anomalies into two categories, overreaction anomalies and underreaction anomalies. Change in institutional ownership is the change in percentage of shares held by institutions. Percent change in the number of institutional owners is the change in the logarithm of the number of institutional owners. The anomaly formation date is June 30 of each year. The *t*-statistics for the differences between the long and short legs are calculated using the Newey-West standard errors. "#>0", "#≫0", "#<0", and "#≪0" denote the number of anomalies where the long-short difference in institutional trading is positive, positive and significant at the 5% level, negative, and negative and significant at the 5% level, respectively. Our sample period is from 1982 to 2021.

Table IA.9
SUE and Window Dressing

Panel A: All Quarters		
	Good News	Bad News
(1) [1, 10]	0.052	−0.021
(2) [q-19, q-10]	0.044	−0.011
(3) [q-9, q]	0.029	−0.022
(1)–(3)	0.023 (1.99)	0.001 (0.12)
(2)–(3)	0.015 (1.64)	0.011 (1.16)
Panel B: Quarter 4		
	Good News	Bad News
(1) [1, 10]	0.040	−0.031
(2) [q-19, q-10]	0.025	0.013
(3) [q-9, q]	0.016	−0.008
(1)–(3)	0.023 (0.98)	−0.023 (−0.95)
(2)–(3)	0.008 (0.42)	0.021 (1.08)
Panel C: Quarters 1, 2 & 3		
	Good News	Bad News
(1) [1, 10]	0.056	−0.017
(2) [q-19, q-10]	0.051	−0.019
(3) [q-9, q]	0.033	−0.027
(1)–(3)	0.023 (1.73)	0.010 (0.71)
(2)–(3)	0.018 (1.67)	0.008 (0.71)

This table examines whether institutions engage in window dressing in response to earnings news as measured by SUE. SUE is the difference between current-quarter earnings per share (EPS) and the EPS four quarters ago, scaled by the standard deviation of unexpected earnings during the past eight quarters. We define the earnings news as good (bad) news if SUE is greater (less) than 0. For each stock on each trading day, we aggregate the transaction data across institutions from the Ancerno database to obtain the aggregate daily net trading and then divide it by shares outstanding. For each news item, we compute the cumulative net institutional trading over different time periods. Specifically, we examine the 10-day window following the new releases (day1 to day10), the last 10 trading days of the quarter [q-9, q], and the 10-day period prior to the last ten trading days of each quarter [q-19, q-10]. Panel A reports full sample results. Panel B reports results for the 4th quarter only. Panel C reports results for the 1st, 2nd and 3rd quarters. In each panel, we report the cumulative net institutional trading during the three time periods, and we also compare the first and the second time period with the quarter-end period, respectively. Numbers in parentheses are *t*-statistics. The sample period for this analysis is from 2003 to 2013.

Table IA.10
TRNA News and Window Dressing

(*continued on next page*)

Table IA.10 (*continued*)

Panel A: All Quarters		
	Good News	Bad News
Panel A: All Quarters		
	Good News	Bad News
(1) [1, 10]	0.063	−0.014
(2) [q-19, q-10]	0.041	−0.012
(3) [q-9, q]	0.044	−0.008
(1)–(3)	0.018 (2.58)	−0.006 (−0.72)
(2)–(3)	−0.003 (−0.61)	−0.004 (−0.59)
Panel B: Quarter 4		
	Good News	Bad News
(1) [1, 10]	0.068	−0.025
(2) [q-19, q-10]	0.028	−0.001
(3) [q-9, q]	0.030	0.004
(1)–(3)	0.039 (2.77)	−0.029 (−1.76)
(2)–(3)	−0.002 (−0.14)	−0.005 (−0.38)
Panel C: Quarters 1, 2 & 3		
	Good News	Bad News
(1) [1, 10]	0.060	−0.010
(2) [q-19, q-10]	0.046	−0.016
(3) [q-9, q]	0.050	−0.013
(1)–(3)	0.010 (1.27)	0.002 (0.24)
(2)–(3)	−0.004 (−0.63)	−0.003 (−0.46)

This table examines whether inst[t]itutions engage in window dressing in response to news. We obtain a comprehensive sample of newswire releases from Thomson Reuters News Analytics (TRNA). We select news items with a relevance score of 1. For each stock on each trading day, we aggregate the transaction data across institutions from the Ancerno database to obtain the aggregate daily net trading and then divide it by shares outstanding. For each news item, we compute the cumulative net institutional trading over different time periods. Specifically, we examine the 10-day window following the new releases (day1 to day10), the last 10 trading days of the quarter [q-9, q], and the 10-day period prior to the last ten trading days of each quarter [q-19, q-10]. Panel A reports full sample results. Panel B reports results for the 4th quarter only. Panel C reports results for the 1st, 2nd and 3rd quarters. In each panel, we report the cumulative net institutional trading during the three time periods, and we also compare the first and the second time period with the quarter-end period, respectively. Numbers in parentheses are *t*-statistics. The sample period for this analysis is from 2003 to 2013.

Table IA.11
Long-term institutional trading and Earnings News

Panel A: Change in institutional ownership								
	ES				SUE			
	>0	<0	Diff	*t*-stat	>0	<0	Diff	*t*-stat
Q+0	0.72%	0.05%	0.67%	5.46	0.51%	0.01%	0.50%	7.99
Q+1	0.47%	0.16%	0.31%	6.47	0.35%	0.05%	0.29%	7.90
Q+2	0.35%	0.18%	0.17%	4.23	0.28%	0.08%	0.20%	4.87
Q+3	0.26%	0.17%	0.09%	3.00	0.24%	0.13%	0.11%	2.45
Q+4	0.20%	0.18%	0.02%	0.67	0.20%	0.15%	0.05%	1.33
Q+5	0.16%	0.19%	−0.03%	−0.70	0.19%	0.16%	0.03%	1.00
Q+6	0.16%	0.19%	−0.03%	−0.98	0.17%	0.17%	0.00%	0.07
Q+7	0.14%	0.13%	0.01%	0.22	0.17%	0.14%	0.03%	1.12
Q+8	0.13%	0.16%	−0.02%	−0.82	0.16%	0.13%	0.03%	1.38
Panel B: Percent change in # of institutional owners								
	ES				SUE			
	>0	<0	Diff	*t*-stat	>0	<0	Diff	*t*-stat
Q+0	3.65%	−0.14%	3.79%	9.60	3.78%	−0.30%	4.08%	14.23
Q+1	2.51%	0.63%	1.88%	5.79	2.84%	0.30%	2.54%	10.21
Q+2	1.94%	0.88%	1.06%	6.41	2.26%	0.72%	1.54%	8.82
Q+3	1.61%	1.18%	0.44%	2.84	1.94%	1.15%	0.78%	5.99
Q+4	1.30%	1.20%	0.10%	0.73	1.64%	1.30%	0.34%	2.33
Q+5	1.14%	1.22%	−0.09%	−0.86	1.54%	1.35%	0.19%	1.59
Q+6	1.07%	1.26%	−0.19%	−1.47	1.45%	1.33%	0.12%	0.73

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Table IA.11 (*continued*)

Panel A: Change in institutional ownership								
Q+7	1.12%	1.10%	0.02%	0.22	1.39%	1.40%	−0.01%	−0.07
Q+8	1.03%	1.01%	0.02%	0.20	1.38%	1.24%	0.14%	1.59

This table examines the relation between earnings news and long-term institutional trading. We obtain monthly stock data from the CRSP and accounting data from Compustat. Quarterly institutional holdings are from Thomson/Refinitiv 13F data. Our sample consists of NYSE, AMEX, and NASDAQ common stocks (with a CRSP share code of 10 or 11). We exclude financial stocks. ES is the earnings surprise, defined as the difference between current-quarter earnings per share (EPS) and analyst earnings forecasts, scaled by the stock price. SUE is the difference between current-quarter earnings per share (EPS) and the EPS four quarters ago, scaled by the standard deviation of unexpected earnings during the past eight quarters. Change in institutional ownership is the change in percentage of shares held by institutions. Percent change in the number of institutional owners is the change in the logarithm of the number of institutional owners. We examine institutional trading during the quarter of the earnings announcement (Q+0) as well as eight quarters (Q+1 to Q+8) subsequent to the earnings announcement quarter. During each quarter, we calculate institutional trading for stocks with positive earnings news and stocks with negative earnings news. We also compute the difference between these two groups. Our sample period is from 1982 to 2021.

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