Taking Sides on Return Predictability

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Abstract

We study how 9 different market participants trade with respect to 130 different stock return anomalies and how each participant's trades predict returns. Retail investors trade against anomalies, while firms' and short sellers' trades agree with anomalies. Institutional portfolios are weighted against anomalies, although some institutions' trades agree with anomalies after the anomaly-measurement date. Retail trades predict returns in the wrong direction, firms' and short sellers' trades predict returns in the intended direction, institutional trades do not robustly predict returns. The return-predictability of trades by retail investors, firms and short sellers can be either mostly or completely explained by anomalies.

Keywords: Trading, return predictability, retail investors, institutions.

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We study how nine different market participants—retail investors, short sellers, firms, and 6 types of institutions—trade with respect to 130 different variables that have been shown to predict the cross-section of stock returns (anomalies) and how each participant's trades forecast returns. A vast literature shows that simple cross-sectional sorts on easy-to-observe characteristics such as earnings surprises (Foster, Olsen, and Shevlin, 1984) and recent past returns (Jegadeesh and Titman, 1993) forecast stock returns. McLean and Pontiff (2016) find that post-publication, anomaly returns decay, but continue to persist. Lewellen (2011), Edelen, Ince, and Kadlec (2016), and Calluzzo, Moneta, and Topaloglu (2019) provide mixed evidence on how institutions trade with respect to some popular anomalies. Drake, Rees, and Swanson (2011) and McLean and Pontiff (2016) find that short sellers target anomaly-shorts. We build on these studies and report several findings that are novel to the literature. Our study provides the broadest investigation of market participation to date.

We follow Engelberg, McLean, and Pontiff (2018 and 2020) and construct a comprehensive index based on 130 anomaly variables, and define longs and shorts as stocks that fall into the top and bottom quintiles of the anomaly index. For each investor type, we calculate changes in ownership over the 1-year and 3-year periods preceding the month that the anomaly variables are constructed. This measurement tells us how each market participant changed their ownership in the years leading up to portfolio formation, and conveys the likelihood that the participant is relatively over- or under-weighted in the anomaly portfolios.

We find that firms and short sellers are the only two participants that build positions that are in agreement with anomaly strategies. Over the 1-year and 3-year periods preceding the month that the anomaly variables are constructed, firms that are eventual anomaly-shorts issue the most shares, while short interest increases in eventual anomaly-shorts and decreases in eventual anomaly-longs.

In contrast, retail investors accumulate future anomaly-short stocks, and reduce holdings in future anomaly-longs. Banks, mutual funds, wealth managers, hedge funds, and insurance companies do not reliably trade one way or the other with respect to anomalies. “Other” or unidentified institutional investors trade like retail investors, accumulating future anomaly-shorts and reducing holdings in future anomaly-longs.

We then study holdings, which we have for institutions and short sellers, but not retail investors or firms.[1] Overall, the holdings data show that short sellers are on the correct side of anomalies, while institutions’ long positions are on the wrong side. That is, short interest is higher in anomaly shorts than anomaly-longs, while all six types of institutions own more anomaly-shorts than anomaly-longs.

Next, we examine trading in anomalies over the 3-month period *subsequent* to time *t*, or the month of anomaly portfolio assignment. Firms that are anomaly-shorts issue the most shares. Short sellers now increase short interest in anomaly-longs and reduce short interest in anomaly-shorts. This likely reflects the fact that short sellers are exiting the favorable positions that they had taken earlier. The magnitudes of short sellers’ trades over this 3-month period are small relative to the short interest measured at the beginning of the period.

Hedge funds and insurance companies now buy the longs and sell the shorts, unwinding the unfavorable positions that they had built previously. Banks, mutual funds, and other

[1] We do not assume that retail holdings = 1 - 13F institutional holdings, as some earlier studies do. Our reasoning is that not all institutions file 13F. Non-13F filers include including some foreign institutions, nonprofits that self-manage their own funds, and institutions that manage less than $100 million.

institutions also trade in this direction; however, their effects are not statistically significant. Moreover, the magnitudes of institutional trades over this 3-month period are small relative to the holdings measured at the beginning of the period. Retail investors continue to trade the worst with respect to anomalies, buying anomaly-shorts and selling anomaly-longs.

Our final set of tests study how the trades of each market participant relate to future stock returns. Consistent with retail investors making poor decisions, retail net buying predicts lower stock returns. The effects are economically meaningful; a one standard deviation increase in retail trading leads to lower monthly returns of 10 to 21 basis points, depending on the horizon over which retail trades are measured. Like most earlier studies (e.g., Sias, Starks, and Titman, 2006), institutional trades tend to not predict returns, with the exception being banks, whose trades predict returns in the wrong direction in most of our specifciations.[2] The trades of both firms and short sellers predict returns in the intended direction. Overall, our results suggest that firms along with short sellers are the "smart money" traders.

We end our study by asking whether anomaly return-predictability can explain the relation between investor trading and future stock returns. To test this hypothesis, we regress stock returns on the 130 anomaly variables. We take the residual from that regression, and regress it on the various trading variables. We find that the return-predictability stemming from retail trades is either much weaker or insignificant. The return-predictability stemming from short sellers' trades is completely insignificant. The return predictability of firm trades is either insignificant or flips sign in our most complete specifications. Hence, the predictability stemming

[2] Within subset of stocks, some studies (e.g., Sias, Starks, and Titman, 2006, and Sias and Whidbee, 2010) find relations between variables constructed with information about institutional holdings and future returns.

from each of these market participants is either partly or completely explained by each group's tendency to trade with or against anomaly variables.

Our paper contributes to several literatures. With respect to institutions and anomalies, Edelen, Ince, and Kadlec (2016) suggest that institutions may contribute to anomalies, as they find that in the year prior to portfolio formation, institutional demand is typically on the *wrong* side of 7 anomaly strategies. We broaden the analysis to 130 anomalies, and also find that institutions' portfolios tend to be weighted against anomalies. Calluzzo, Moneta, and Topaloglu (2019) use a sample of 14 anomaly strategies, and find that some institutions, mainly hedge funds, follow anomaly strategies post-portfolio formation in their long positions, but only after an anomaly is highlighted in an academic publication. This result helps explain McLean and Pontiff's (2016) post-publication decay in anomaly returns. In our post-portfolio formation tests, we also find that some institutions, namely hedge funds and insurance companies, tend to trade in the right direction with respect to an index of 130 anomalies.

Earlier studies find that short sellers are on the profitable side of anomaly strategies. Drake, Rees, and Swanson (2011) find that short sellers target stocks that anomaly variables suggest should be shorted. McLean and Pontiff (2016) also find that short sellers target anomaly-shorts, and further find that anomaly-shorting increases after an anomaly has been highlighted in an academic publication. We add new insights to this literature as well. We find that short sellers build positions during the 3-year period prior to anomaly-portfolio formation, and start to exit soon after. We also find that return-predictability stemming from short interest can explained by the information in anomaly variables. Boehmer, Jones, and Zhang (2008) show that institutions account for about 75% of short-sales, while individuals account for less than 2%, so monthly changes in short interest largely reflects hedge funds. Interestingly, our results suggest that hedge funds do much better in their short positions than their long positions, both with respect to anomalies and future stock returns.

The relation we find between share issuance and anomaly expected returns contradicts some findings in earlier work. For example, Baker and Wurgler (2002) find that more profitable firms issue fewer shares, while Pontiff and Woodgate (2008) find that smaller firms issue fewer shares. In these two cases, firms are trading against the profitability and size anomalies. Baker and Wurgler (2002) also find that high market-to-book firms issue more shares, so in this case firms are trading with anomalies. Our findings show that overall, firms tend to trade with anomalies.[3]

Our firm issuance results lend support to two diametrically opposed strands of the literature. The first strand is the behavioral corporate finance literature. It asserts that firms issue (repurchase) shares when stock prices are overvalued (undervalued). Papers in this genre include Loughran and Ritter (1995), Baker and Wurgler (2000 and 2002), and Graham and Harvey (2002). In this setting, our anomaly index reflects mispricing, and overvalued firms (anomaly-shorts) are issuing more shares in response to mispricing.

The second strand of literature argues that firms that issue (repurchase) shares have lower (higher) expected returns due to risk. This literature includes papers on production-based asset pricing (e.g., Cochrane, 1991 and forthcoming, and Zhang, 2005) and real options (e.g., Carlson, Fisher, and Giammarino, 2006). In these frameworks, our anomaly index proxies for

[3] Greenwood and Hanson (2012) find that for several anomaly strategies, when the difference in net share issues between the anomaly-sells and anomaly-buys is greater (i.e., anomaly-sells' net issues – anomaly-buys' net issues), the anomaly's subsequent long-short return spread is greater.

management's assessment of expected returns or changes in expected returns due to the exercise of a real option

Our paper also contributes to the literature on retail investors. Previous literature on retail investors fails to find a consensus regarding individuals' exposure to individual anomaly characteristics. Barber and Odean (2013) review research that shows that individuals trade such that they forego momentum anomaly returns, whereas Graham and Kumar (2006) show that individuals overweight high dividend yield stocks thus tilting exposure to dividend anomalies. Hirshleifer, Myers, Myers, and Teoh (2008) show that individual investors are neutral with respect to the post-earnings drift. We find that, in general, retail investors tend to trade against anomalies.

Barber and Odean (2013) provide a comprehensive review on the performance of retail investors. Studies in this literature tend to use weekly retail trade imbalances (buys – sells / buys + sells) as measures of retail trading. Barber and Odean (2013) point out that there is tension in the literature, as over short horizons (e.g., 1-week, up to 1-month) retail trades predict returns in the right direction (see Kaniel, Saar, and Titman (2008), Barber, Odean, and Zhu (2009a), Kaniel, Saar, Liu, and Titman (2012), Kelly and Tetlock (2013), Boehmer, Jones, and Zhang (2020)), whereas over longer horizons (e.g., 1-year) retail trades predict returns opposite to the intended direction (see Odean (1999), Barber and Odean (2000), Grinblatt and Keloharju (2000), Hvidkjaer (2008), and Barber, Odean, and Zhu (2009a and 2009b)). Our retail trading variable is different from the retail trade imbalance variable used in these earlier studies, as our variable reflects *accumulated* trades over 1-year and 3-year horizons, scaled by shares outstanding. Our variables predict lower returns, while controlling for the weekly trade imbalance. Taken together, these results show that temporary spikes in retail trading (i.e., weekly trade imbalances) predict returns in the intended direction, whereas retail trading aggregated over long horizons (our variables) predicts returns in the wrong direction. We also find that the predictability from our retail trading variables can be explained by anomalies, while the predictability from the weekly trade imbalance variables is not.

1. Sample and Data

1.1 Trading Overview

Our trading measures are calculated over frequencies of 1-quarter, 1-year, and 3-years. Our trading measures reflect changes in ownership over each horizon. The participants we consider are retail investors, firms, short sellers, and 6 types of institutions that report their holdings on form 13F. Given that our variables are constructed over horizons of 1 quarter or longer, they do not reveal potentially informed intra-quarter trading such as in Puckett and Yan (2011) and Kacpercyzk, Sialm, and Zhang (2008). Derivative holdings can also be an avenue for informed trading (Aragon and Spencer, 2012), and these are also not reflected in our trading variables.

1.2 Retail Trading

We estimate retail trading via the methodology developed in Boehmer, Jones, and Zhang (2020), which identifies marketable orders originating from retail investors. Boehmer et. al. (2020) show that due to the modern characteristics of market structure and rules of Regulation NMS (National Market System), one can identify retail orders based on the sub-penny pricing of the execution. Retail marketable buy orders are likely to be internalized and receive sub-penny price improvement such that the trade price falls slightly below a whole cent. Conversely, retail marketable sell orders are likely to be internalized and receive sub-penny price improvement such that the trade price falls slightly above the whole cent. Thus, as outlined by Boehmer et. al. (2020), we calculate the fraction of the penny associated with the transaction price: $Z_{it} \equiv 100 * \text{mod}(P_{it}, 0.01)$ where P_{it} is the transaction price in the stock. Trades reported to FINRA TRF (exchange code 'D') with a Z_{it} in the range of (0.6, 1) are identified as buys by retail traders. Similarly, trades reported to FINRA TRF with a Z_{it} in the range of (0, 0.4) are identified as sells by retail traders. Consistent with Boehmer et. al. (2020), we do not identify trades with Z_{it} in the range of (0.4,0.6) as retail trades, since some advanced order types, such as pegged orders, can result in transaction prices at or near half pennies that do not involve retail traders.[4]

We diverge from Boehmer et. al. (2020) in how we aggregate buys and sells from retail traders to form our retail trading measure. We calculate the daily percent of equity purchased by retail traders as (retail buys – retail sells / shares outstanding as reported by CRSP. We then aggregate this measure to periods ranging from 3 months to 3 years. We choose to scale net retail buying volume by shares outstanding because we believe a measure of the percent of equity purchased by retailers will act as a better proxy for how much investors overweight or underweight stocks, and thus their exposure to the anomaly portfolios that we include in this

[4] To our knowledge, this retail measure is the only viable retail measure that can be constructed from commercially available data. Hvidkjaer (2008) proposes a measure based on trade size, but this method is no longer viable since the proliferation of market fragmentation and algorithmic trading prevents the identification of the original order size.

study. This scaling also facilitates direct comparisons to our other trading measures (describe below), which are also scaled by shares outstanding.

In order to construct our retail trading variable, we require that for every month during the relevant period, the stock must have at least one retail-initiated trade. This ensures that the stock was actively traded, and was not newly listed or temporarily delisted. The identification of retail trade relies on Regulation NMS, so we restrict our sample to the period of October 2006 through December 2017. We find the share of identified retail initiated trades rises beginning in October 2006. We exclude stocks with prices under $1, measured one month before the anomaly portfolios are constructed. Such low-priced stocks are often excluded in anomaly studies. Lastly, we restrict our sample to common stock with share code 10 or 11 and listed on the NYSE, NYSE MKT (formerly Amex), or NASDAQ.

Retail limit order are not internalized. There also may be retail market orders that are not internalized. As such, we are aggregating a subset of the population of retail trades, and the resulting variable may be nosier than the 13F variables. That stated, Boehmer et. al. (2020) validate this methodology using actual retail trade data from both Kelley and Tetlock (2013) and NASDAQ, and find that this retail trading estimate is highly correlated with actual retail trades.

Table 1 shows that our 1-year and 3-year lagged trading measures have mean values of 0.03% and 0.05%, respectively. This is sensible, as retail investors accumulate some stocks, and sell others, so on average retail trading is close to zero. Similarly, our 3-month trading measure has a mean of 0.00%.

1.3. Institutional Trading

We obtain institutional holdings data from quarterly SEC 13F and S12 data, and use these data to estimate our trading variables. Not all institutions file 13F. U.S. institutions that manage less than $100 million in 13F securities are not required to file form 13F. Foreign institutions are only required to file 13F if they both pass the $100 million threshold and "use any means or instrumentality of United States interstate commerce in the course of their business."[5] French (2008) reports that according to Fed Flow of Funds data, foreign institutions own 16.3% of U.S. equities, while 13F reflects foreign institutional ownership of 7.6%, so the majority of foreign institutional holdings are not reflected in 13F. Non-profits that self-direct their portfolios also do not have file 13F. Some institutions apply for SEC exemption from disclosing some profitable positions (Agarwal, Jiang, Tang, and Yang, 2013, and Aragon, Hertzel, and Shi, 2013), so these positions are also not reflected in 13F. For these reasons, we do not assume that 1 – 13F holdings is equal to retail holdings.

We estimate mutual fund, bank, insurance, wealth management, hedge fund, and "other" (unclassified) institutional trading using changes in institutional holdings reported in 13F filings.[6] We utilize 13F filings documented by Thomson Reuters and supplement them with SEC 13F filings in order to correct known issues with Thomson Reuters data in the later parts of our sample. We use the following methods to classify institutions into one of six types:

[5] See the rule here: www.sec.gov/divisions/investment/13ffaq.htm

[6] Bushee (1998) and Cella, Ellul, and Giannetti (2013) bifurcate 13F data into 9 subgroups. Since we include 3 non-13F participants, our decision to focus on six 13F groups is intended to improve exposition.

- To identify mutual fund institutions, we merge mutual fund holdings reported in S12 filings and documented by Thomson Reuters with 13F filings. We classify the number of shares reported by mutual funds as shares held by mutual fund institutions.
- We identify banks and insurance companies using type codes provided by Brain Bushee.[7] The holdings that are denoted as bank holdings are typically from trust accounts that are managed by a financial advisor.
- If an institution is not a bank, insurance company, and does not have any mutual funds, we then classify them as either a wealth management or a hedge funds using text criteria based on institution names.[8]
- Any remaining institutions are classified as "Other" institutions.

Regarding holdings classified as "Other," these holdings appear to be directed by large investment banks that do not have commercial banking operations. We expect that most of these shares are held in separate accounts or collective investment trust (CIT). Separate accounts are non-comingled managed accounts whereas CITs are commingled. CITs have the appearance of a mutual fund, and are often used in workplace retirement plans. Some of the holdings classified as "Other" may reflect proprietary trading.

A visual inspection of the institutions classified as *Hedge Funds*, *Wealth Managers*, and *Other*, affirms that our textual classification does a reasonable job. We have also experimented with classifications based on hedge fund lists and hedge fund databases, such that the designation as

[7] Brian Bushee's classification schem can be found here: http://acct.wharton.upenn.edu/faculty/bushee/IIclass.html
[8] In order to identify wealth managements, we perform case insensitive searches for "Wealth Manag", "Wealth MGNT", "Private", "PRVT" and "advisor". We then perform case insensitive searches for the remaining institutions "LLC", "L.L.C." "L L C", "L. L. C.", "LP", "L.P", "L P", "L. P", or "Partner" to identify hedge funds.

a hedge fund occurs before our sample starts.[9] These exercises produce very similar results. All of the methods that we investigated avoid designating firms as hedge funds that are assigned to a list or database after a period of good performance, which would bias our analysis towards the conclusion that hedge funds accumulate positions in well-performing stocks.

To estimate the institutional trading of each firm, we scale the aggregated shares held by each institution type by the number of shares outstanding. We then calculate the change in the percentage of shares outstanding held by each type of institution, over periods of 3-months, 1-year and 3-years, the same horizons as our retail trading variables.

1.4. Short Sellers

Stocks exchanges report end-of-month short interest. We retrieve this information from Compustat. As we previously note, Boehmer, Jones, and Zhang (2008) document that the majority of short positions are held by hedge funds. We calculate *Short Seller Trading* as changes in short interest scaled by shares outstanding.[10] We sign this variable such that increases in short interest result in negative values of *Short Seller Trading* and decreases in short interest (net closing of short positions) result in positive values of *Short Seller Trading.* Table 1 shows that the

[9] Specifically, we utilize two different hedge fund classifications from prior literature. First, we use the hedge fund identification scheme of Cella, Ellul, and Giannetti (2013). Secondly, we use the identification scheme of Agarwal, Fos and Jiang (2013). They manually identify the universe of hedge funds that had made 13F filings as of 2008 so as to mitigate selection biases of self-reporting hedge funds. We also attempted to augment the Agarwal, Fos and Jiang (2013) hedge fund list with text-based logic to identify hedge funds that first file 13Fs later than 2008. In all of these cases, our results with respect to hedge funds do not materially change.

[10] For the *Short Seller Trading* measure, we utilize shares outstanding as reported by Compustat. After auditing, we believe the Compustat reported shares outstanding better aligns with Compustat short interest data and thus results in less errors due to stock splits than a measure reliant on CRSP data. For all other trading measures, including *Firm Trading*, which most directly relies upon shares outstanding, we utilize CRSP reported shares outstanding.

mean of the 3-month, 1-year and 3-year *Short Seller Trading* variables are -0.03%, -0.18% and -0.49% respectively. Thus, in our sample, aggregate short interest increased.

1.5. Firm Trading

Firm trading is measured as the percentage change in the firm's shares outstanding (adjusted for splits and stock dividends). This follows the method in Pontiff and Woodgate (2008) and McLean, Pontiff, and Watanabe (2009). We scale the change in shares (share issues minus share repurchases) by shares outstanding, and sign this variable such that positive values of *Firm Trading* indicate a reduction in shares outstanding, i.e., a firm buying back its shares. We create this variable each month using the CRSP reported shares outstanding adjusted for splits and stock dividends. Similar to our institutional trading variables, shares outstanding data may only substantively update on a quarterly basis, when firms release financial reports regarding the completion of share repurchases. Table 1 shows that the mean of 3-month, 1-year and 3-year *Firm Trading* variables are -0.86%, -3.92% and -11.42% respectively. Thus, in our sample, the *average* firm issued more shares than it repurchased (although larger firms may have been net repurchasers, as has been reported in the media).

1.6. Trading Among the Market Participants

Some readers ask whether our 9 participants encompass virtually all participants. If this were the case, then an adding constraint yields one of the trading groups redundant. As we explain earlier, this is not the case, as non-profits, most foreign institutions, and other exempted institutions do not report their holdings on form 13F, and the holdings of these participants can be substantial.

Panel B of Table 1 reports average cross-sectional correlations among the various trading variables. The trading variables are each measured over a 3-year period. The first column shows that the correlations between retail investors and the other investors are negative, telling us that negative retail investors tend to trade against the other market participants. The retail correlations are strongest with firms and short sellers, as these correlations are -0.33 and -0.19, respectively.

Short sellers also trade against the other market participants. The correlations are especially strong with mutual funds, banks, hedge funds, and other institutional investors, ranging from -0.13 to -0.21. The correlation between short sellers and firms is only 0.01, so these two participants do not trade against each other. As discussed above, the correlation between firms and retail traders are particularly strong, with a value of -0.33. The correlation between firms and institutions are weak and generally negative, ranging from -0.07 to 0.01. This negative correlation between institutions and firms is consistent with Ince and Kadlec (2020), who find that share issues and repurchases are an increasingly important counterparty to 13F institutions' trades.

Panel C of Table 1 presents quarterly trading autocorrelations. Most participant's exhibit negative autocorrelation, thus more buying is typically followed by less buying or selling. The biggest exception are retail investors who show strong quarter-to-quarter persistence, 0.25. Firms and wealth managers also exhibit persistence, but at lower levels.

1.7. Stock Return Anomalies

We use a sample of 130 stock return anomalies that are documented in published academic studies. This builds on the 97-anomaly sample used in McLean and Pontiff (2016) and Engelberg, McLean and Pontiff (2018) and the 125-anomaly sample used in Engelberg, McLean and Pontiff (2020). All of the anomaly variables can be constructed with data from CRSP, Compustat, and IBES. We exclude anomalies based on institutional investors, short sellers, and share issues and repurchases.

To create the anomaly variables, stocks are sorted each month on each of the anomaly-characteristics. We define the long and short side of each anomaly strategy as the extreme quintiles produced by the sorts. Some of our anomalies are indicator variables (e.g, credit rating downgrades). For these cases, there is only a long or short side, based on the binary value of the indicator. We remake the anomaly portfolios each month.

Like Engelberg, McLean, Pontiff, (2018 and 2020), we create an anomaly index *Net*, which is the difference between the number of long and short anomaly portfolios that a stock belongs to in a given month. As an example, a *Net* value of 10 in month *t* means that a stock belongs to 10 more anomaly-long portfolios than anomaly-short portfolios in month *t*. Table 1 shows that in our sample, *Net* has a mean value of -1.30, and a standard deviation of 8.90.

In Table 2, we sort stocks each month on *Net* into quintiles. We report the average *Net* values for each quintile at time *t*, and for each of the three years before and after time *t*. One takeaway from Table 2 is that all of the action happens in the extreme quintiles. Moving from the low to high *Net* quintiles, the average *Net* values are -10.4, -1.0, 0.9, 2.0, and 8.5. So, there is not much difference in *Net* values among quintiles 2, 3, and 4, but a large difference, of 18.9, between quintiles 1 and 5.

Table 2 also shows that *Net* is highly persistent in all of the quintiles. In the low *Net* quintiles, the average *Ne*t values are -8.5, -8.9, -9.2, and -10.4, for times *t-3*, *t-2*, *t-1*, and *t*, and then -9.3, -9.0, and -8.7, for times *t+1*, *t+2*, and *t+3*. For the high *Net* quintiles, the average *Ne*t values are 6.6, 7.0, 7.3, and 8.5, for times *t-3*, *t-2*, *t-1*, and *t*, and then 7.3, 7.0, and 6.7, for times *t+1*, *t+2*, and *t+3*. The three middle quintiles show persistence as well.

2. Main Findings

2.1 Trading Prior to Anomaly Portfolio Formation

In this section of the paper we ask how each market participant trades prior to stocks being assigned to anomaly portfolios. If a stock is an anomaly-buy (or anomaly-sell) at time *t*, the time of portfolio formation, which participants increase or decrease their ownership of the stock prior to time *t*? We answer this question in Table 3. Panel A studies trading 1 year prior to time *t*, whereas Panel B studies trading 3 years prior to time *t*. As we explain in the previous section, the trading variables are changes in ownership scaled by shares outstanding, i.e., buys minus sells scaled by shares outstanding.

The findings in Table 3 show that retail investors tend to do the worst with respect to anomalies, as they build positions in eventual anomaly-shorts and reduce holdings in eventual anomaly-longs. Short sellers do the best; they increase short interest in the eventual anomaly-shorts and reduce short interest in eventual anomaly-longs. Firms are net issuers of all types of stock, however firms that are anomaly-shorts issue the most shares. Note that firms are not like the other trading groups, as they may need to raise capital to operate. Institutions are a mixed bag. None of them consistently get things right. Insurance companies do the best. Overall, the results here suggest that firms and short sellers are the smart money.

Examining the results in more detail, Panel A shows that, in the year prior to anomaly portfolio formation, retail investors accumulate anomaly-shorts and reduce their holdings in anomaly-longs. The value in the anomaly-short portfolio is 0.10%, whereas the value in the anomaly-long portfolio is -0.02%. The difference between these two values is statistically significant. Other institutional investors accumulate both anomaly-longs and anomaly-shorts, but they accumulate more of the shorts. The trading values for other institutional investors are 0.32% and 0.79% for the anomaly-longs and anomaly-shorts, respectively. Mutual funds reduce their holdings in both anomaly-longs and anomaly-shorts; however, they sell the longs more. The values in the anomaly-long and anomaly-short portfolios for mutual funds are -0.21% and -0.13%, respectively. Wealth managers and banks appear to be relatively neutral, their trading does not go with or against anomalies in a noticeable way.

Insurance companies buy anomaly-longs and sell anomaly-shorts. The values for the long and short portfolios are 0.00% and -0.07%, respectively. Hedge funds accumulate all types of stocks during this period, but accumulate more anomaly-longs. The values are 0.69% and 0.81% in the 4th and 5th (anomaly-long) quintiles, while the value is 0.58% in the anomaly-short portfolio.

Short sellers increase short interest in anomaly-shorts and reduce short interest in anomaly-longs. The values are -0.50% and 0.12% in the anomaly-short and anomaly-long portfolios, respectively. Firms are net issuers of shares in all five of the portfolios, however firms that are anomaly-shorts issue more shares than do firms that are anomaly-longs. Net share issuers are equal to 4.68% for anomaly-shorts and 3.40% for anomaly-longs.

Panel B examines the 3-year trading measures. The same patterns emerge as in Panel A. The differences in Panel B are in most cases larger than the differences in Panel A, showing that the associated trading patterns persisted for more than one year. If the patterns were of the same magnitude as in Panel A, then we could attribute all of the trading to trading in the final year before portfolio formation. However, the fact that we observe stronger patterns in Panel B, it suggests consistent trading for more than one year.

In Panel B, retail investors buy anomaly-shorts and sell-anomaly-longs. The short and long values are 0.21% and -0.03%, respectively, for retail investors. Mutual funds sell all stocks in all five quintiles, however they sell almost four times as much long as shorts. The mutual fund trading values are -0.22% and -0.79% for the anomaly-shorts and anomaly-longs, respectively. Banks display a similar pattern to mutual funds, with trading values of -0.54% and -0.84% in anomaly-shorts and anomaly-longs. Other institutional investors accumulate stocks in all 5 quintiles, however they accumulate far more anomaly-shorts than anomaly-longs, as the values are 3.79% and 1.08% for the short and long portfolios. Wealth managers now sell slightly more anomaly-shorts than anomaly-longs, while insurance companies sell slightly more longs than shorts.

Hedge funds show a different pattern than in Panel A, where they bought more longs than shorts. In Panel B, hedge funds buy both anomaly-shorts and anomaly-longs, however they buy more shorts than longs. The values are 2.72% and 2.16% in the in the short and long portfolios, respectively. Taken together with the results in Panel A, this shows that hedge funds buy more shorts than longs in years t-3 and t-2, but then buy more longs than shorts in year t-1, perhaps because they realize the mispricing.

Brunnermeier and Nagel (2004) document that hedge funds were overexposed to internet glamour stocks during the internet bubble and then reduced their positions before the bubble burst. If this apparent ability to time mispricing extends more generally, we would expect hedge funds to increase ownership in anomaly-longs and decrease ownership in anomaly-shorts, yet we do not observe this here.

Short sellers increase short interest in shorts and reduce it in longs. The values are 0.30% and -1.30% for the longs and shorts respectively. Firms are net issuers across all five of the quintiles, however firms that are anomaly-shorts issue more shares than do firms that are longs. Firms that are shorts issue shares equal to 13.87% of shares outstanding, while firms that are longs issue 9.87%. For both firms and short sellers, the magnitudes are large in Panel B than in Panel A, suggesting that these trading patterns were persistent over the entire 3-year period.

2.3 Portfolio Holdings

In this section of the paper we study the holdings of the various market participants. We can observe holdings for institutions and short sellers, but not for firms and retail investors. To perform our holdings analyses, we sort forms into quintiles based on *Net*, and then tabulate the percentage of shares outstanding held by each market participant. Overall, the findings show that only short sellers are well-positioned with respect to anomalies. All 6 types of institutions are positioned against anomalies. Although we do not control for firms size here, in earlier drafts we report holdings regressions where we control for price and size, and the findings are the same, i.e., institutions hold more anomaly-shorts than anomaly-longs.

The first row of Table 4 shows that mutual funds own on average 14.2% of shares in anomaly-shorts and 8.2% of shares in anomaly-longs, i.e., mutual funds;' holdings contradict anomaly strategies. Similarly, banks own 8.1% of shares outstanding in the shorts and 4.3% in the longs, hedge funds own 16.9% of the shorts and 13.3% of the longs respectively, while "other" or unclassified institutional investors own 32.6% of the shorts and 21.3% of the longs. Insurance companies and wealth managers have smaller holdings, but both own significantly less shorts than longs.

Short interest averages 6.5% in anomaly-shorts and 2.8% in anomaly-longs. This is consistent with the findings in the earlier tables, where short sellers are shown to sell anomaly-shorts and buy anomaly-longs. Hence, short sellers position themselves to take advantage of anomaly strategies, whereas institutions do the opposite. As we mention in the Introduction, it is likely that most short positions are held by hedge funds. Interestingly, we see here that hedge funds do not position themselves correctly with respect to anomalies on the long-side.

These results lend support to the view that the long-run accumulated trade variable that we use in Table 3 is a decent proxy over- or underweight in anomaly long and shorts. The differences between holdings is similar to the differences in the three-year measures. The signs correspond for all participants except insurance companies and wealth managers. Overall, the results here tell the same story as the earlier tables—institutional investors tend to be on the wrong side of anomaly strategies, while short sellers are on the right side

2.4 Trading After Anomaly Portfolio Formation

In Table 3, we examine trading during the 1-year and 3-years prior to anomaly portfolio assignment. In Table 4, we studied holdings at the time of portfolio assignment. In Table 5, we study trading over the 3-months *subsequent* to portfolio assignment. That is, we study how the various market participants trade with respect to observable anomaly variables, e.g., do retail investor buy stocks that are currently anomaly-longs and sell stocks that are currently anomaly-shorts?

Most anomaly strategies are shown to predict returns from periods ranging from 1 month to 12 months. Our *Net* variable is designed to predict returns over the subsequent month, but it does predict returns over the next 12 months (not reported in tables). Hence, it makes sense to buy high *Net* stocks and sell low *Net* stocks over the measurement period that we study here, which is the 3 months subsequent to portfolio assignment.

Table 5 shows that after the time of portfolio formation, retail investors continue their tendency to buy anomaly-shorts and sell anomaly-longs. The values for retail trading are 0.00% and -0.01% for the anomaly-long and anomaly-short portfolios, respectively. The difference between the high minus low has a t-stat of 1.8, and is thus only statistically significant at the 10% threshold.

Institutional investors do better now. Hedge funds and insurance companies buy significantly more longs than shorts. Mutual funds, banks, and other institutional investors also buy more longs than shorts, although the differences are not statistically significant. Wealth managers buy more shorts than longs, but they are the only institutional investor to do so.

Short sellers now reduce short interest in anomaly-shorts. They increase short interest in most of the other quintiles, but reduce it in anomaly-shorts. Taken together with the results in Tables 2 and 3, the results here show that short sellers begin to exit their anomaly positions, perhaps too quickly, as anomaly-shorts do have low returns over this period. However the reduction in short interest here is small compared to the short interest reported in Table 4, so this is a slow exit. Finally, firms are net issuers across all 5 quintiles, but more so the anomaly-shorts, so firms continue to trade in agreement with anomaly strategies.

2.6 Predicting Stock Returns

In this section of the paper we study how retail, institutional, short seller, and firm trading predicts stock returns. Earlier studies show that firm trading (repurchases minus issues) predicts higher returns (e.g., Pontiff and Woodgate (2006) and McLean, Pontiff, and Watanabe (2009)). Earlier studies also show that over long-horizons, increases in institutional ownership forecast lower returns (see Gutierrez and Kelly (2009), Dasgupta, Prat, and Verado (2011), and Edelen, Ince, and Kadlec (2016)). Papers by Dechow et al. (2001) and Duan, Hu, and McLean (2009) show that high levels of short interest portend low returns. As we mention in the Introduction, several papers show that weekly retail-trade imbalances, which are measured as buys minus sells scaled by buys plus sells, predict returns in the intended direction over short horizons (e.g., 1-month or less). We therefore include weekly retail-trade imbalances in our regressions.

Table 6 reports our findings for the 1-year trading variables. The trading variables are measured over months *t-11* through *t*, while price and size (used a controls) are measured at time *t*. The weekly trade imbalance is measured during the last week of month *t*. The dependent variable is the monthly stock return in month *t+1* expressed in basis points.

The results show that the effects of each variable on stock returns are fairly independent of one another, as the coefficients are mostly similar in the univariate and multivariate specifications.

The first 11 regressions are univariate regressions, with *Net* and each trading variable tested independently. Consistent with earlier studies, the coefficients for *Net*, the weekly trade imbalance, firm trading, and short seller trading are all positive and significant. New to the literature, the coefficient for bank trading is negative and significant. The coefficients for the other institutions are insignificant.

The regressions reported in the last two columns include *Net* and all of the variables, with the regression in the final column also controlling for price and size. In both of these regressions, the coefficients for *Net*, the weekly trade imbalance, firm trading, and short seller trading are all positive and significant, while the coefficient for banks is negative and significant. In the final specification, the coefficient for retail trading is negative, and at the borderline for significance.

With respect to economic significance, in the regression reported in the final column, the coefficient on retail trading is -985.60 (*t*-statistic = -1.65). The 1-year retail trading variable has a standard deviation of 1.01%, so a one standard deviation increase in retail trading leads to a decrease in monthly returns of 10 basis points, which is a meaningful effect. The coefficient for the firm trading variable is 176.12 (*t*-statistic = 3.53), so a one standard deviation increase in the firm trading variable implies a monthly return that is higher by 24 basis points.

The coefficient for the weekly trade imbalance is 118.44, so a one standard deviation increase in this variable implies a monthly return that is higher by 27 basis points. The short selling coefficient show an increase in monthly return of 12 basis points, per standard deviation increase. A one standard deviation increase in *Net* yields an increase in monthly return of 24 basis points. Most of the anomaly variables used in *Net* are post-publication (our sample begins in October of 2006), and McLean and Pontiff (2016) find that anomaly predictability is about half as large post-publication.

The coefficient for bank trading in the final specification is -459.37. A one standard deviation increase in bank trading therefore yields a decrease in subsequent monthly return of about 15 basis points. As we mention above, banks are the only institution to predict returns in our sample, and to the best of our knowledge such return-predictability has not been previously linked to bank trades.

Table 7 studies return-predictability with the 3-year trading variables, and produces stronger findings for several of the measures. As in Table 6, short seller trading and firm trading predict returns in the intended direction. The retail trading coefficient is negative and significant in all specifications. Measuring retail trades over a longer horizon therefore appears to be important, as the retail trading coefficient is not significant in Table 6, where trading is measured over one-year. In the most complete specification reported in the final column, a one standard deviation increase in retail trading reflects a 21-basis point decrease in returns.

The trades of mutual funds, banks, insurance companies, and other institutions are negative and significant in the univariate regressions, but not in the more complete regressions reported in the final two columns: all four coefficients are insignificant. The coefficient for wealth managers is positive and significant in the two complete specifications, but not in the univariate regression. Overall, the findings suggest that institutions' trades do not robustly predict returns.

2.7 Explaining Trading Return-Predictability with Anomalies

In this last table we examine whether anomaly return-predictability can explain the relation between investor trading and future stock returns. In the earlier tables, we control for anomaly predictability with the composite anomaly variable *Net*. In this table, we take the 130 anomaly variables used to create *Net*, and regress stock returns on the entire 130. We then take the residual from that regression, and regress the residual on the variables used in Tables 6 and 7.

Table 8 shows that retail trading, which was found to be a strong predictor in Table 7, is a much weaker predictor if anomaly returns are more completely controlled for. In Panel A, the 1-year retail trading coefficients are insignificant. In Panel B, the 3-year retail trading coefficients are less significant as compared to those reported in Table 7. In Panel B in the most complete specification reported in the final column, the retail trading coefficient has a *t*-statistic of -1.96. In contrast, in Table 7, which estimates the same specification using raw stock returns, the *t*-statistic for the 3-year retail trading variable is -3.88. The underperformance if retail trades is therefore largely explained by retail investors tendency to trade against anomalies.

The weekly order imbalance variable remains highly significant in these specifications. Hence, whatever information is reflected in these trade spikes is largely orthogonal to the information reflected in the anomaly variables. The findings here therefore suggest that when retail investors accumulate (reduce) positions in stocks over long horizons, they do so in stocks that are overvalued (undervalued) according to anomaly variables. However, when retail investors trade aggressively in the short run, they tend to buy (sell) stocks in which the current price is too low (high), and such information is not reflected in anomalies. It may very well be that different populations of retail investors create these two very different findings.

The trades of short sellers are insignificant. Hence, the predictability stemming from short sellers is explained by the group's tendency to trade with anomaly variables. The firm trading variable is insignificant in the most complete specification in Panel A, and flips sign and the most complete specification in Panel B. The positive relation between firm trading and return-predictability can therefore also be explained by firms trading with anomalies.

3. Conclusions

In the broadest study of market participation to date, we study how the trades of retail investors, institutional investors, short sellers, and firms—relate to stock return anomalies and future stock returns. We find that firms and short sellers appear to be the smart money. Both firms and short sellers tend to trade with anomaly strategies, i.e., both heavily sell anomaly-shorts, but not anomaly-longs, and the trades of firms and short-sellers predict returns in the intended direction. The return-predictability stemming from firms' and short sellers' trades can be explained by both groups tendency to trade with anomalies.

Retail investors do the worst. They buy anomaly-shorts and sell-anomaly-longs, and their trades predict returns in the unintended direction. A good deal of the return-predictability stemming from retail trades can be explained by retail investors' tendency to trade against anomalies.

Institutions can be described as neutral, at best. Their holdings are tilted against anomalies, meaning institutions hold more anomaly-shorts than longs, although they begin to unwind these positions after the portfolio formation date. None of the six institutional types' trades robustly predict returns.

References

Agarwal, V., Fos, V. and Jiang, W., 2013, Inferring reporting-related biases in hedge fund databases from hedge fund equity holdings. Management Science 59(6), 1271-1289.

Agarwal, Vikas, Wei Jiang, Yuehua Tang and Baozhong Yang, 2013, Uncovering Hedge Fund Skill from the Portfolio Holdings They Hide, Journal of Finance 68, 739-783.

Aragon, George, Michael Hertzel, and Zhen Shi, 2013, Why do hedge funds avoid disclosure? Evidence from confidential 13F filings, Journal of Financial and Quantitative Analysis, 1499-1518.

Aragon, George O., and J. Spencer Martin, 2012, A unique view of hedge fund derivatives usage: Safeguard or speculation? Journal of Financial Economics 105, 436–456.

Ball, Raymond and Phillip Brown, 1968, "An Empirical Evaluation of Accounting Income Numbers", Journal of Accounting Research 6, 159-178.

Baker, Malcolm, and Jeffrey Wurgler, 2000, The equity share in new issues and aggregate stock returns, Journal of Finance 55, 2219–2257.

Baker, M. and Wurgler, J. (2002), Market Timing and Capital Structure. The Journal of Finance, 57, 1-32.

Barber, B. M., and Odean, T. (2000). Trading is hazardous to your wealth: The common stock investment performance of individual investors. Journal of Finance, 55, 773–806.

Barber, B. M., Odean, T., & Zhu, N. (2009a). Do retail trades move markets?. Review of Financial Studies, 22, 151–186.

Barber, B. M., Odean,T., & Zhu, N. (2009b). Systematic noise. Journal of Financial Markets, 12, 469–547.

Barber, Brad and Odean, Terrance, (2013), The Behavior of Individual Investors, Chapter 22, p. 1533-1570, Elsevier.

Blume, Marshal E. and Frank, Husic, 1973, "Price, beta, and exchange listing," Journal of Finance 28, 283-299.

Boehmer, Ekkehart, Charles M. Jones, and Xioyan Zhang, 2008, Which shorts are informed?, Journal of Finance 63, 491-527.

Boehmer, Ekkehart, Charles M. Jones, and Xioyan Zhang, 2020, Tracking Retail Investor Activity, Working Paper

Brunnermeier, Markus and Stefan Nagel, 2004, Hedge funds and the technology bubble, Journal of Finance 59, 2013-2040.

Bushee, B. J. 1998. The influence of institutional investors on myopic R&D investment behavior. *Accounting Review* 73, 305–33.

Calluzzo, Paul, Fabio Moneta and Selim Topaloglu, 2019, Institutional Trading and Anomalies, *Management Science* 65, 4555-4574.

Carlson, M., A. Fisher, and R. Giammarino. 2006. Corporate Investment and Asset Price Dynamics: Implications for SEO Event Studies and Long-Run Performance. *Journal of Finance* 61, 1009–34.

Cristina Cella, Andrew Ellul, Mariassunta Giannetti, 2013, Investors' Horizons and the Amplification of Market Shocks, *The Review of Financial Studies* 26, 1607–1648,

Cochrane, J. H. 1991. Production-Based Asset Pricing and the Link Between Stock Returns and Economic Fluctuations. *Journal of Finance* 46:209–37.

Cochrane, J. H., forthcoming, Rethinking production under uncertainty, Review of Asset Pricing Studies.

Dasgupta, A., Prat, A., Verardo, M., 2011. Institutional Trade Persistence and Long-Term Equity Returns. Journal of Finance, 66, 635-653.

Daniel, Kent and Sheridan Titman, 2006, Market Reactions to Tangible and Intangible Information, Journal of Finance 61, 1605-1643.

Dechow, P., A. Hutton, L. Meulbroek, and R. Sloan, 2001. Short sellers, fundamental analysis and stock returns, Journal of Financial Economics 61, 77-106.

De Long, J Bradford, Andrei Shleifer, Lawrence Summers, and Robert Waldmann, 1990a, Noise Trader Risk in Financial Markets, Journal of Political Economy, 98, 703-38.

De Long, J Bradford, Andrei Shleifer, Lawrence Summers, and Robert Waldmann, 1990b, Positive Feedback Investment Strategies and Destabilizing Rational Speculation, Journal of Finance, 45, 379-95.

Drake, M., L. Rees and E. Swanson, 2011. Should investors follow the prophets or the bears? Evidence on the use of public information by analysts and short sellers. The Accounting Review 86: 101-130.

Duan, Ying, Gang Hu, and R. David McLean, 2009, “Costly Arbitrage and Idiosyncratic Risk: Evidence from Short Sellers,” Journal of Financial Intermediation 19, 564-579.

Engelberg, Joseph, David McLean, and Jeffrey Pontiff, 2018, Anomalies and News, Journal of Finance 73, 1971-2001.

Engelberg, Joseph, David McLean, and Jeffrey Pontiff, 2020, Analysts and Anomalies, Journal of Accounting and Economics 69.

Edelen, Roger, Ozgur Ince, and Gregoy Kadlec, 2016, Institutional Investors and Stock Return Anomalies, Journal of Financial Economics 119, 472-488.

Foster, G., C. Olsen, and T. Shevlin. 1984, Earnings Releases, Anomalies, and the Behavior of Security Returns, The Accounting Review, 574-603.

French, K., 2008. Presidential address: the cost of active investing. The Journal of Finance 63, 1537–1573.

Grinblatt, M., and Keloharju, M. (2000). The investment behavior and performance of various investor types: A study of Finland’s unique data set. Journal of Financial Economics, 55, 43–67.

Graham, J., & Kumar, A. (2006). Do Dividend Clienteles Exist? Evidence on Dividend Preferences of Retail Investors. *The Journal of Finance, 61*, 1305-1336.

Gutierrez, R.C., Kelley, E.K., 2009. Institutional herding and future stock returns. Working paper, University of Oregon and University of Arizona.

Hirshleifer, D., Myers, J. N., Myers, L. A., & Teoh, S. H. (2008). Do individual investors drive post-earnings announcement drift? Direct evidence from personal trades. *Accounting Review, 83*, 1150–1521.

Hvidkjaer, S. (2008). Small trades and the cross-section of stock returns. Review of Financial Studies, 21, 1123–1151.

Ince, Ozgur S. and Kadlec, Gregory B. and McKeon, Stephen B., 2018, Institutional Counterparties and Performance, Working Paper

Jegadeesh, Narasimhan and Sheridan Titman, 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. Journal of Finance 48, 65–91.

Kaniel, R., Liu, S., Saar, G., & Titman, S. (2012). Individual Investor Trading and Return Patterns around Earnings Announcements. Journal of Finance, 67, 639–680.

Kaniel, R., Saar, G., & Titman, S. (2008). Individual investor trading and stock returns. Journal of Finance, 63, 273–310.

Kacperczyk, Marcin, Clemens Sialm, and Lu Zheng, 2008, Unobserved actions of mutual funds, *Review of Financial Studies* 21, 2379–2416.

Kelley, E. K., & Tetlock, P. C. 2013, How Wise Are Crowds? Insight from Retail Orders and Stock Returns. Journal of Finance 68, 1229-1265.

Lewellen, Jonathan, 2011, Institutional investors and the limits of arbitrage, Journal of Financial Economics 102, 62-80.

Loughran, Tim, and Jay Ritter, 1995, The new issues puzzle, Journal of Finance 50, 23–51

McLean, R. David and Jeffrey Pontiff, 2016, "Does academic research destroy stock return predictability?," *Journal of Finance* 71, 5-32.

Nosfinger, John R. and Richard W. Sias, 2002, "Herding and Feedback Trading by Institutional and Individual Investors," Journal of Finance 54, 2263-2295.

Odean, T. (1998). Volume, volatility, price, and profit when all traders are above average. *Journal of Finance, 53*, 1887–1934.

Odean,T. (1999). Do investors trade too much? American Economic Review, 89, 1279–1298.

Pontiff, Jeffrey, and Woodgate, Artemiza (2008). Share issuance and cross-sectional returns. The Journal of Finance 63 no. 2, 921-945.

Puckett, Andy and Sterling Yan, 2011, The interim trading skills of institutional investors, Journal of Finance 66, 601-633.

Sias, Richard W. and Laura T. Starks, *2006,* Changes in Institutional Ownership and Stock Returns: Assessment and Methodology, *The Journal of Business* 79, 2869-2910.

Sias, Richard & Whidbee, David, 2010, Insider Trades and Demand by Institutional and Individual Investors. *Review of Financial Studies* 23, 1544-1595.

U.S. Department of Education, 2019, National Center for Education Statistics. *Digest of Education Statistics, 2017* (NCES 2018-094), Chapter 3.

Zhang, L. 2005. The Value Premium. *Journal of Finance* 60(1), 67–103.

Table 1: Descriptive Statistics of Variables

Panel A of this table provides descriptive statistics for the variables used in the study. Panel B reports average cross-sectional correlations of our main variables of interest. Panel C reports the variables' autocorrelations. We construct the *Retail Trading* variables by summing the daily percentage of common equity purchased by retail traders for the relevant period. Daily percentage of equity purchased by retail traders is calculated as (retail buyer initiated - retail seller initiated) / shares outstanding. Retail buyer and seller-initiated trades are identified by sub-penny pricing as described by Boehmer et al. (2020). *Mutual Fund Trading, Bank Trading, Insurance Company Trading, Wealth Management Trading, Hedge fund Trading,* and *Other Institutional Trading* are calculated as the changes in categorized 13F reported holdings. *Short Seller Trading* is calculated as the negative change in short interest / shares outstanding. Thus, a positive value of *Short Seller Trading* indicates a decrease in the short interest and vice versa. *Firm Trading* is calculated as the negative change in shares outstanding / beginning of period shares outstanding. Thus, a positive value of *Firm Trading* indicates a decrease in the shares outstanding and vice versa. All trading variables are winsorized at the 1% level. Weekly order imbalance is calculated as the average of (retail buyer initiated - retail seller initiated) / (retail buyer initiated + retail seller initiated) for the last five trading days of the month. We use 130 cross-sectional anomalies, which are described in the paper's appendix. At the end of each month, stocks are sorted on each anomaly characteristic (e.g., size, book-to-market, accruals). We use the extreme quintiles to define the long side and short side of each anomaly strategy. Some anomalies are indicator variables (e.g., credit rating downgrades); for these anomalies, there is only a long or short side, based on the binary value of the indicator. We exclude anomalies based on 13F data, short interest and share issuances since they are used for the construction of our institutional trading, *Short seller Trading* and *Firm Trading* measures. For each firm-month observation, we sum the number of long-side and short-side anomaly portfolios that the firm belongs to and calculate net as the total long - short indicators. Price and size are reported as of the time of the anomaly stock sorts. Size is the CRSP reported market capitalization of common equity. *Net Residual* is the residuals from monthly returns regressed on the 130 anomaly indicator variables. These residuals represent the monthly return not explained by which anomaly portfolios an equity belongs to at the beginning of the month.

Panel A: Descriptive Statistics of Firm-Month Observations								
Variable	**Obs.**	**Mean**	**Std. Dev.**	**1^{st} %ile**	**25^{th} %ile**	**Median**	**75^{th} %ile**	**99^{th} %ile**
Retail Trading$_{t-11,t}$	435,686	0.03%	1.01%	-2.09%	-0.34%	-0.07%	0.19%	4.33%
Retail Trading$_{t-35,t}$	306,930	0.05%	2.14%	-4.01%	-0.82%	-0.22%	0.36%	10.21%
Retail Trading$_{t,t+3}$	496,370	0.00%	0.36%	-1.03%	-0.12%	-0.02%	0.07%	1.46%
Mutual Fund Trading$_{t-11,t}$	461,529	-0.09%	6.20%	-20.17%	-1.74%	0.01%	1.68%	18.85%
Mutual Fund Trading$_{t-35,t}$	415,885	-0.42%	8.77%	-26.21%	-3.81%	0.00%	3.18%	23.69%
Mutual Fund Trading$_{t,t+3}$	484,209	-0.08%	4.03%	-14.74%	-0.53%	0.00%	0.54%	13.62%
Mutual Fund Ownership$_{t}$	492,146	11.50%	10.14%	0.00%	2.52%	9.94%	17.66%	41.60%
Bank Trading$_{t-11,t}$	461,529	-0.14%	3.35%	-10.68%	-1.34%	0.00%	1.23%	9.33%
Bank Trading$_{t-35,t}$	415,885	-0.67%	5.01%	-15.16%	-3.10%	-0.19%	1.79%	12.73%
Bank Trading$_{t-35,t+3}$	484,209	-0.05%	1.77%	-6.38%	-0.36%	0.00%	0.40%	5.15%
Mutual Fund Ownership$_{t}$	492,146	6.60%	5.96%	0.00%	1.37%	5.32%	10.40%	23.81%
Insurance Company Trading$_{t-11,t}$	461,529	-0.04%	1.44%	-4.95%	-0.34%	0.00%	0.32%	4.34%
Insurance Company Trading$_{t-35,t}$	415,885	-0.17%	2.12%	-7.17%	-0.76%	0.00%	0.53%	5.84%
Insurance Company Trading$_{t,t+3}$	484,209	-0.01%	0.71%	-2.49%	-0.10%	0.00%	0.09%	2.26%
Insurance Company Ownership$_{t}$	492,146	1.82%	2.14%	0.00%	0.14%	1.23%	2.57%	9.87%
Wealth Management Trading$_{t-11,t}$	461,529	0.00%	0.18%	-0.47%	0.00%	0.00%	0.00%	0.30%
Wealth Management Trading$_{t-35,t}$	415,885	-0.03%	0.44%	-1.40%	0.00%	0.00%	0.00%	0.68%
Wealth Management Trading$_{t,t+3}$	484,209	0.00%	0.06%	-0.14%	0.00%	0.00%	0.00%	0.09%
Wealth Management Ownership$_{t}$	492,146	0.06%	0.42%	0.00%	0.00%	0.00%	0.00%	1.57%
Hedgefund Trading$_{t-11,t}$	461,529	0.71%	7.33%	-20.54%	-2.18%	0.20%	3.37%	24.04%
Hedgefund Trading$_{t-35,t}$	415,885	2.48%	10.13%	-25.85%	-2.13%	1.51%	7.02%	33.12%
Hedgefund Trading$_{t,t+3}$	484,209	0.15%	4.37%	-13.64%	-1.07%	0.00%	1.22%	15.03%
Hedgefund Ownership$_{t}$	492,146	15.14%	12.10%	0.00%	5.83%	13.06%	21.73%	52.75%
Other Institutional Trading$_{t-11,t}$	461,529	0.85%	9.03%	-26.17%	-2.90%	0.39%	4.52%	27.60%
Other Institutional Trading$_{t-35,t}$	415,885	2.59%	12.63%	-34.20%	-3.50%	2.00%	8.80%	38.38%
Other Institutional Trading$_{t,t+3}$	484,209	0.15%	5.01%	-15.83%	-1.37%	0.02%	1.66%	15.65%
Other Institutional Ownership$_{t}$	492,146	27.27%	17.06%	0.00%	12.67%	28.01%	40.17%	66.24%
Short Seller Trading$_{t-11,t}$	467,759	-0.18%	3.83%	-13.39%	-1.23%	-0.01%	1.00%	11.84%
Short Seller Trading$_{t-35,t}$	417,163	-0.49%	5.41%	-18.47%	-2.10%	-0.03%	1.37%	15.81%
Short Seller Trading$_{t,t+3}$	488,251	-0.03%	2.02%	-7.02%	-0.52%	0.00%	0.53%	6.55%
Short Seller Ownership$_{t}$	495,496	-4.69%	5.60%	-27.03%	-6.37%	-2.77%	-0.91%	0.00%

Firm Trading$_{t-11,t}$	481,696	-3.92%	13.59%	-71.94%	-2.74%	-0.60%	0.42%	14.49%
Firm Trading$_{t-35,t}$	434,763	-11.41%	30.82%	-158.67%	-14.16%	-2.53%	2.29%	31.36%
Firm Trading$_{t,t+3}$	500,832	-0.86%	4.38%	-24.34%	-0.44%	-0.06%	0.00%	5.30%
Weekly Order Imbalance$_t$	508,738	-3.34%	22.96%	-63.75%	-16.79%	-1.85%	9.78%	56.20%
Net$_t$	509,365	-1.30	8.90	-23	-7	-1	5	20
Price$_t$	509,237	$69.19	$2,685.46	$1.07	$6.65	$16.09	$33.75	$164.32
Size$_t$	509,237	$4,587,209	$20,300,000	$8,611	$119,429	$480,886	$2,053,875	$80,900,000
Return$_{t+1}$	508,808	64bp	1535bp	-3810bp	-597bp	36bp	656bp	4612bp
Net Residual$_{t+1}$	502,984	0bp	15bp	-39bp	-7bp	-1bp	6bp	45bp

Panel B: Average Cross-Sectional Correlations									
Variable	*Retail Trading*$_{t-35,t}$	*Mutual Fund Trading*$_{t-35,t}$	*Bank Trading*$_{t-35,t}$	*Insurance Company Trading*$_{t-35,t}$	*Wealth Management Trading*$_{t-35,t}$	*Hedge fund Trading*$_{t-35,t}$	*Other Institutional Trading*$_{t-35,t}$	*Short Seller Trading*$_{t-35,t}$	*Firm Trading*$_{t-35,t}$
Mutual Fund Trading$_{t-35,t}$	-0.04								
Bank Trading$_{t-35,t}$	0.02	0.12							
Insurance Company Trading$_{t-35,t}$	-0.01	0.09	0.14						
Wealth Management Trading$_{t-35,t}$	0.02	0.00	0.02	0.00					
Hedge fund Trading$_{t-35,t}$	-0.06	-0.03	0.07	0.04	0.00				
Other Institutional Trading$_{t-35,t}$	-0.07	0.19	0.11	0.10	0.01	0.09			
Short Seller Trading$_{t-35,t}$	-0.19	-0.13	-0.17	-0.10	0.00	-0.15	-0.21		
Firm Trading$_{t-35,t}$	-0.33	-0.06	-0.06	-0.04	-0.03	-0.07	-0.05	0.01	
Net$_{t}$	-0.07	-0.03	-0.02	0.00	0.00	-0.04	-0.09	0.13	0.08

Panel C: Quarterly Autocorrelations								
Retail Trading	*Mutual Fund Trading*	*Bank Trading*	*Insurance Company Trading*	*Wealth Management Trading*	*Hedgefund Trading*	*Other Institutional Trading*	*Short Seller Trading*	*Firm Trading*
0.25	-0.31	-0.09	-0.06	0.07	-0.18	-0.13	-0.10	0.15

Table 2: Net Time Series by Net Anomaly Quintiles

This table reports average time series *Net* indicators for quintile sorts of *Net* anomaly indicators. For each month, quintiles are formed by sorting observations by *Net*. Due to the discrete nature of *Net*, this forms five quintiles of differing size. To create the *Net* anomaly variable, we use 130 cross-sectional anomalies, which are described in the paper's appendix. We exclude anomalies based on 13F data and share issuances since they are used for the construction of our *Institutional Trading* and *Firm Trading* measures. For each stock-month observation, we sum up the number of long-side and short-side anomaly portfolios that the stock belongs to and calculate *Net* as equal to the number of long portfolios minus number of short portfolios.

	Net_t Quintile				
Reported Variable:	**Lo**	**2**	**3**	**4**	**Hi**
Net_{t-3}	-8.5	-0.8	0.7	1.4	6.6
Net_{t-2}	-8.9	-0.9	0.7	1.5	7.0
Net_{t-1}	-9.2	-0.9	0.7	1.6	7.3
Net_t	-10.4	-1.0	0.9	2.0	8.5
Net_{t+1}	-9.3	-0.9	0.7	1.6	7.3
Net_{t+2}	-9.0	-0.9	0.7	1.5	7.0
Net_{t+3}	-8.7	-0.9	0.7	1.4	6.7

Table 3: Net Anomaly Indicators on Past Trading

This table reports average trading by various trader types over 1 (3) year(s) prior to quintile sorts of *Net* anomaly indicators. The *Retail Trading* is expressed as the percentage of common equity net purchased by retail traders during the relevant time period. We construct the retail net buying variables by summing the daily percentage of common equity purchased by retail traders for the relevant period. Daily percentage of equity purchased by retail traders is calculated as (retail buyer initiated - retail seller initiated) / shares outstanding. Retail buyer and seller-initiated trades are identified by sub-penny pricing as described by Boehmer et al. (2020). *Mutual Fund Trading, Bank Trading, Insurance Company Trading, Wealth Management Trading, Hedge fund Trading,* and *Other Institutional Trading* are calculated as the changes in categorized 13F reported holdings between the most recent filing and the filing 1 (3) years prior to the most recent filing. *Short Seller Trading* is calculated as the negative change in short interest / shares outstanding. Thus, a positive value of *Short Seller Trading* indicates a decrease in the short interest and vice versa. *Firm Trading* is calculated as the negative change in shares outstanding / beginning of period shares outstanding. Thus, a positive value of *Firm Trading* indicates a decrease in the shares outstanding and vice versa. All trading variables are winsorized at the 1% level. We use 130 cross-sectional anomalies, which are described in the paper's appendix. At the end of each month, stocks are sorted on each anomaly characteristic (e.g., size, book-to-market, accruals). We use the extreme quintiles to define the long side and short side of each anomaly strategy. Some anomalies are indicator variables (e.g., credit rating downgrades); for these anomalies, there is only a long or short side, based on the binary value of the indicator. We exclude anomalies based on 13F data, short interest and share issuances since they are used for the construction of our institutional trading, *Shortseller Trading* and *Firm Trading* measures. For each stock-month observation, we sum up the number of long-side and short-side anomaly portfolios that the stock belongs to and calculate *Net* as equal to the number of long portfolios minus number of short portfolios. Newey-West standard errors are utilized for the t-statistics in parentheses. The sample period is from 2006:10 to 2017:12. *, **, and *** indicate significance at the 10%, 5% and 1% respectively.

Table 3 (Continued)

Panel A: Prior 1-Year Trading							
	Net$_t$ Quintile						
Reported Variable:	Lo	2	3	4	Hi	Hi - Lo	t-stat
Retail Trading$_{t-11,t}$	0.10%	0.00%	-0.03%	-0.01%	-0.02%	-0.12%	-5.0
Mutual Fund Trading$_{t-11,t}$	-0.13%	-0.02%	-0.01%	-0.02%	-0.21%	-0.08%	-0.3
Bank Trading$_{t-11,t}$	-0.13%	0.04%	0.18%	-0.09%	-0.17%	-0.03%	-0.2
Insurance Company Trading$_{t-11,t}$	-0.09%	-0.05%	-0.09%	-0.06%	0.00%	0.09%	3.7
Wealth Management Trading$_{t-11,t}$	0.00%	0.00%	0.01%	0.02%	0.00%	0.00%	-0.6
Hedgefund Trading$_{t-11,t}$	0.58%	0.38%	0.51%	0.69%	0.81%	0.22%	1.6
Other Institutional Trading$_{t-11,t}$	1.07%	0.52%	0.27%	0.31%	0.46%	-0.61%	-1.9
Short Seller Trading$_{t-11,t}$	-0.50%	-0.05%	0.12%	0.10%	0.12%	0.62%	4.6
Firm Trading$_{t-11,t}$	-4.68%	-3.58%	-3.32%	-3.55%	-3.40%	1.28%	5.4

Panel B: Prior 3-Year Trading							
	Net$_t$ Quintile						
Reported Variable:	Lo	2	3	4	Hi	Hi - Lo	t-stat
Retail Trading$_{t-35,t}$	0.21%	-0.04%	-0.11%	-0.06%	-0.03%	-0.24%	-4.2
Mutual Fund Trading$_{t-35,t}$	-0.22%	-0.22%	-0.08%	-0.26%	-0.79%	-0.58%	-1.2
Bank Trading$_{t-35,t}$	-0.54%	-0.04%	0.27%	-0.38%	-0.84%	-0.30%	-0.9
Insurance Company Trading$_{t-35,t}$	-0.17%	-0.18%	-0.22%	-0.17%	-0.15%	0.02%	0.6
Wealth Management Trading$_{t-35,t}$	-0.02%	-0.01%	0.00%	0.01%	-0.01%	0.00%	0.8
Hedgefund Trading$_{t-35,t}$	2.72%	1.65%	1.48%	1.89%	2.16%	-0.57%	-1.0
Other Institutional Trading$_{t-35,t}$	3.79%	1.91%	1.39%	1.24%	1.08%	-2.71%	-11.8
Short Seller Trading$_{t-35,t}$	-1.30%	-0.18%	0.28%	0.15%	0.30%	1.60%	5.4
Firm Trading$_{t-35,t}$	-13.87%	-9.89%	-9.51%	-9.92%	-9.87%	4.00%	3.4

Table 4: Ownership by Net Anomaly Quintiles

This table reports average monthly ownership level for quintile sorts of *Net* anomaly indicators. For each month, quintiles are formed by sorting observations by *Net*. Due to the discrete nature of *Net*, this forms five quintiles of differing size. Newey-West standard errors with 12 lags are utilized for the t-statistics reported for Hi-Lo averages. Institutional ownerships reported are from 13F filings. We categorize these institutions as described in the data section. *Short Seller Ownership* is calculated as short interest divided by shares outstanding. *Short Seller Ownership* is signed to make interpretation consistent with other ownership variables. All ownership measures are winsorized at the 1% level. To create the *Net* anomaly variable, we use 130 cross-sectional anomalies, which are described in the paper's appendix. We exclude anomalies based on 13F data and share issuances since they are used for the construction of our *Institutional Trading* and *Firm Trading* measures. For each stock-month observation, we sum up the number of long-side and short-side anomaly portfolios that the stock belongs to and calculate *Net* as equal to the number of long portfolios minus number of short portfolios.

	Net_t Quintile						
Reported Variable:	**Lo**	**2**	**3**	**4**	**Hi**	**Hi - Lo**	**t-stat**
Mutual Fund Ownership$_t$	14.2%	7.3%	2.5%	5.1%	8.2%	-6.0%	-12.7
Bank Ownership$_t$	8.1%	6.2%	5.1%	5.5%	4.3%	-3.8%	-13.1
Insurance Ownership$_t$	2.2%	1.5%	0.9%	1.1%	1.2%	-1.0%	-20.2
Wealth Management Ownership$_t$	0.1%	0.1%	0.1%	0.1%	0.0%	0.0%	-2.4
Hedge fund Ownership$_t$	16.9%	11.8%	8.5%	11.7%	13.3%	-3.6%	-17.7
Other Institutional Ownership$_t$	32.6%	23.1%	18.1%	22.0%	21.3%	-11.4%	-27.3
Short Seller Ownership$_t$	-6.5%	-4.2%	-2.0%	-2.6%	-2.8%	3.6%	21.5

Table 5: Future Trading on Net Anomaly Indicators

This table reports average trading by various trader types over 3 months after quintile sorts of *Net* anomaly indicators. We construct the retail net buying variables by summing the daily percentage of common equity purchased by retail traders for the relevant period. Daily percentage of equity purchased by retail traders is calculated as (retail buyer initiated - retail seller initiated) / shares outstanding. Retail buyer and seller-initiated trades are identified by sub-penny pricing as described by Boehmer et al. (2020). *Mutual Fund Trading, Bank Trading, Insurance Company Trading, Wealth Management Trading, Hedge fund Trading,* and *Other Institutional Trading* are calculated as the changes in categorized 13F reported holdings between the most recent filing and the filing 3 months after the most recent filing. *Short Seller Trading* is calculated as the negative change in short interest / shares outstanding. Thus, a positive value of *Short Seller Trading* indicates a decrease in the short interest and vice versa. *Firm Trading* is calculated as the negative change in shares outstanding / beginning of period shares outstanding. Thus, a positive value of *Firm Trading* indicates a decrease in the shares outstanding and vice versa. All trading variables are winsorized at the 1% level. We use 130 cross-sectional anomalies, which are described in the paper's appendix. At the end of each month, stocks are sorted on each anomaly characteristic (e.g., size, book-to-market, accruals). We use the extreme quintiles to define the long side and short side of each anomaly strategy. Some anomalies are indicator variables (e.g., credit rating downgrades); for these anomalies, there is only a long or short side, based on the binary value of the indicator. We exclude anomalies based on 13F data, short interest and share issuances since they are used for the construction of our institutional trading, *Short Seller Trading* and *Firm Trading* measures. For each stock-month observation, we sum up the number of long-side and short-side anomaly portfolios that the stock belongs to and calculate *Net* as equal to the number of long portfolios minus number of short portfolios. Newey-West standard errors are utilized for the t-statistics in parentheses. The sample period is from 2006:10 to 2017:12. *, **, and *** indicate significance at the 10%, 5% and 1% respectively.

Following Quarter Trading							
	Net_t Quintile						
Reported Variable:	**Lo**	**2**	**3**	**4**	**Hi**	**Hi - Lo**	**t-stat**
Retail Trading$_{t,t+3}$	0.00%	-0.01%	-0.01%	0.00%	-0.01%	-0.01%	-1.8
Mutual Fund Trading$_{t,t+3}$	-0.14%	-0.05%	-0.02%	0.01%	-0.04%	0.10%	1.1
Bank Trading$_{t,t+3}$	-0.09%	-0.01%	0.06%	0.00%	-0.02%	0.06%	1.3
Insurance Company Trading$_{t,t+3}$	-0.03%	-0.02%	-0.04%	-0.02%	0.00%	0.03%	3.9
Wealth Management Trading$_{t,t+3}$	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	-0.6
Hedgefund Trading$_{t,t+3}$	0.09%	0.09%	0.11%	0.12%	0.19%	0.10%	2.7
Other Institutional Trading$_{t.t+3}$	0.09%	0.10%	0.05%	-0.04%	0.16%	0.07%	0.7
Short Seller Trading$_{t,t+3}$	0.02%	-0.01%	0.01%	-0.03%	-0.04%	-0.06%	-1.7
Firm Trading$_{t.t+3}$	-0.94%	-0.84%	-0.84%	-0.88%	-0.84%	0.10%	1.6

Table 6: Returns Following 1-Year Trading Variables

This table reports results from a Fama-Macbeth regression of monthly stock returns on the *Net* anomaly indicator, *Retail Trading, Mutual Fund Trading, Bank Trading, Insurance Company Trading, Wealth Management Trading, Hedge fund Trading, Other Institutional Trading, Short Seller Trading* and *Firm Trading* aggregated through the 1 year prior to the month of the anomaly stock sorts, *log(Price)* at the month of the anomaly stock sorts, and *log(Size)* as measured by the log of the CRSP reported market capitalization of common equity at the month of the anomaly stock sorts. Monthly Returns are reported by CRSP and denoted as basis points. The *Retail Trading* is expressed as the percentage of common equity net purchased by retail traders during the relevant time period (.01 = 1% of common equity). We construct the retail net buying variables by summing the daily percentage of common equity purchased by retail traders for the relevant period. Daily percentage of equity purchased by retail traders is calculated as (retail buyer initiated - retail seller initiated) / shares outstanding. Retail buyer and seller-initiated trades are identified by sub-penny pricing as described by Boehmer et al. (2020). *Mutual Fund Trading, Bank Trading, Insurance Company Trading, Wealth Management Trading, Hedge fund Trading,* and *Other Institutional Trading* are calculated as the changes in categorized 13F reported holdings between the most recent filing and the filing 1 year prior to the most recent filing. *Short Seller Trading* is calculated as the negative change in short interest / shares outstanding. Thus, a positive value of *Short Seller Trading* indicates a decrease in the short interest and vice versa. *Firm Trading* is calculated as the negative change in shares outstanding / beginning of period shares outstanding. Thus, a positive value of *Firm Trading* indicates a decrease in the shares outstanding and vice versa. All trading variables are winsorized at the 1% level. Weekly order imbalance is calculated as the average of (retail buyer initiated - retail seller initiated) / (retail buyer initiated + retail seller initiated) for the last five trading days of the month. To create the *Net* anomaly variable, we use 130 cross-sectional anomalies, which are described in the paper's appendix. We exclude anomalies based on 13F data, short interest and share issuances since they are used for the construction of our institutional trading, *Short Seller Trading* and *Firm Trading* measures. For each stock-month observation, we sum up the number of long-side and short-side anomaly portfolios that the stock belongs to and calculate *Net* as equal to the number of long portfolios minus number of short portfolios. Newey-West standard errors are utilized for the t-statistics in parentheses. The sample period is from 2006:10 to 2017:12. *, **, and *** indicate significance at the 10%, 5% and 1% respectively.

Table 6 (Continued)

	Dependent Variable: $Return_{t+1}$												
Net_t	1.93***											2.15***	2.74***
	(3.15)											(3.35)	(3.30)
Retail $Trading_{t-11,t}$		-1649.55										-814.22	-985.60
		(-1.55)										(-1.09)	(-1.65)
Mutual Fund $Trading_{t-11,t}$			-112.23									-25.93	-2.85
			(-1.16)									(-0.30)	(-0.04)
Bank $Trading_{t-11,t}$				-548.99***								-421.23**	-359.37**
				(-2.66)								(-2.33)	(-2.36)
Insurance Company $Trading_{t-11,t}$					-494.53							-369.13	-353.31
					(-1.48)							(-1.25)	(-1.28)
Wealth Management $Trading_{t-11,t}$						3448.05						3799.96	3957.00
						(1.32)						(1.36)	(1.46)
Hedge fund $Trading_{t-11,t}$							32.19					26.47	58.26
							(0.29)					(0.23)	(0.70)
Other Institutional $Trading_{t-11,t}$								-110.64				-60.53	-59.07
								(-1.21)				(-0.77)	(-0.97)
Short Seller $Trading_{t-11,t}$									506.06***			306.53**	309.81***
									(3.53)			(2.61)	(2.80)
Firm $Trading_{t-11,t}$										224.48***		184.13***	176.12***
										(3.97)		(3.27)	(3.48)
Weekly Order $Imbalance_t$											116.48***	118.09***	118.44***
											(8.53)	(8.27)	(8.09)
$\log(Size_t)$													9.92*
													(1.79)
$\log(Price_t)$													-9.49
													(-0.42)
Constant	76.28	81.40	76.97	82.71	82.17	82.32	77.11	79.07	81.00	87.12	78.97	87.37	-22.33
	(1.36)	(1.36)	(1.39)	(1.48)	(1.48)	(1.48)	(1.40)	(1.43)	(1.49)	(1.59)	(1.54)	(1.53)	(-0.29)
Lags for Newey-West SE's	12	12	12	12	12	12	12	12	12	12	1	12	12
No. Time Periods	134	124	135	135	135	135	135	135	135	135	135	123	123
N	508,808	438,492	464,085	464,085	464,085	464,085	464,085	464,085	470,467	484,426	511,679	401,586	401,574

Table 7: Returns Following 3-Year Trading Variables

This table reports results from a Fama-Macbeth regression of monthly returns on the *Net* anomaly indicator, *Retail Trading, Mutual Fund Trading, Bank Trading, Insurance Company Trading, Wealth Management Trading, Hedge fund Trading, Other Institutional Trading, Short Seller Trading,* and *Firm Trading* aggregated through the 3 years prior to the month of the anomaly stock sorts, *log(Price)* at the month of the anomaly stock sorts, and *log(Size)* as measured by the log of the CRSP reported market capitalization of common equity at the month of the anomaly stock sorts. Monthly Returns are reported by CRSP and denoted as basis points. The *Retail Trading* is expressed as the percentage of common equity net purchased by retail traders during the relevant time period (.01 = 1% of common equity). We construct the retail net buying variables by summing the daily percentage of common equity purchased by retail traders for the relevant period. Daily percentage of equity purchased by retail traders is calculated as (retail buyer initiated - retail seller initiated) / shares outstanding. Retail buyer and seller initiated trades are identified by sub-penny pricing as described by Boehmer et al. (2020) *Mutual Fund Trading, Bank Trading, Insurance Company Trading, Wealth Management Trading, Hedge fund Trading,* and *Other Institutional Trading* are calculated as the changes in categorized 13F reported holdings between the most recent filing and the filing 3 years prior to the most recent filing. *Short Seller Trading* is calculated as the negative change in short interest / shares outstanding. Thus, a positive value of *Short Seller Trading* indicates a decrease in the short interest and vice versa. *Firm Trading* is calculated as the negative change in shares outstanding / beginning of period shares outstanding. Thus, a positive value of *Firm Trading* indicates a decrease in the shares outstanding and vice versa. All trading variables are winsorized at the 1% level. Weekly order imbalance is calculated as the average of (retail buyer initiated - retail seller initiated) / (retail buyer initiated + retail seller initiated) for the last five trading days of the month. To create the *Net* anomaly variable, we use 130 cross-sectional anomalies, which are described in the paper's appendix. We exclude anomalies based on 13F data, short interest and share issuances since they are used for the construction of our institutional trading, *Short Seller Trading* and *Firm Trading* measures. For each stock-month observation, we sum up the number of long-side and short-side anomaly portfolios that the stock belongs to and calculate *Net* as equal to the number of long portfolios minus number of short portfolios. Newey-West standard errors are utilized for the t-statistics in parentheses. The sample period is from 2006:10 to 2017:12. *, **, and *** indicate significance at the 10%, 5% and 1% respectively.

Table 7 (Continued)

	Dependent Variable: $Return_{t+1}$												
Net_t	1.93***											2.37***	2.73***
	(3.15)											(3.86)	(4.33)
$Retail\ Trading_{t-35,t}$		-1649.51***										-1006.56***	-988.47***
		(-4.39)										(-3.60)	(-3.88)
$Mutual\ Fund\ Trading_{t-35,t}$			-57.85**									-11.56	-2.78
			(-2.23)									(-0.40)	(-0.10)
$Bank\ Trading_{t-35,t}$				-316.24***								-128.38**	-78.14
				(-3.07)								(-2.62)	(-1.55)
$Insurance\ Company\ Trading_{t-35,t}$					-294.27***							19.44	12.04
					(-2.62)							(0.27)	(0.18)
$Wealth\ Management\ Trading_{t-35,t}$						565.17						1408.59**	1338.76**
						(1.03)						(2.53)	(2.44)
$Hedge\ fund\ Trading_{t-35,t}$							-38.27					44.81	50.00
							(-0.65)					(0.89)	(1.05)
$Other\ Institutional\ Trading_{t-35,t}$								-108.52**				-24.84	-34.18
								(-2.39)				(-0.73)	(-0.96)
$Short\ Seller\ Trading_{t-35,t}$									452.41***			274.96***	282.19***
									(8.42)			(4.66)	(5.02)
$Firm\ Trading_{t-35,t}$										94.37***		27.47**	29.37**
										(5.60)		(2.09)	(2.08)
$Weekly\ Order\ Imbalance_t$											116.48***	105.17***	104.71***
											(8.53)	(12.50)	(15.95)
$log(Size_t)$													5.33
													(1.50)
$log(Price_t)$													-3.35
													(-0.49)
Constant	76.28	126.54***	80.06*	85.20*	86.68*	86.26*	85.94*	89.18**	88.89**	93.57**	78.97	134.50***	74.95**
	(1.36)	(5.74)	(1.83)	(1.91)	(1.93)	(1.93)	(1.96)	(2.00)	(2.07)	(2.16)	(1.54)	(6.74)	(2.15)
Lags for Newey-West SE's	12	36	36	36	36	36	36	36	36	36	1	36	36
No. Time Periods	134	100	135	135	135	135	135	135	135	135	135	99	99
N	508,808	309,576	418,149	418,149	418,149	418,149	418,149	418,149	419,611	437,245	511,679	281,522	281,519

Table 8: Residual Return Regressions

This table reports results from a Fama-Macbeth regression of monthly residual stock returns on the various trading variables. Residual stock returns are the residuals from monthly monthly returns, expressed in basis points, regressed on the 130 anomaly indicator variables. These residuals represent the monthly return not explained by the anomaly variables. *Retail Net Buying* is expressed as the percentage of common equity net purchased by retail traders during the relevant time period (.01 = 1% of common equity). We construct the retail net buying variables by summing the daily percentage of common equity purchased by retail traders for the relevant period. Daily percentage of equity purchased by retail traders is calculated as (retail buyer initiated - retail seller initiated) / shares outstanding. Retail buyer and seller-initiated trades are identified by sub-penny pricing as described by Boehmer et al. (2020). *Mutual Fund Trading, Bank Trading, Insurance Company Trading, Wealth Management Trading, Hedge fund Trading,* and *Other Institutional Trading* are calculated as the changes in categorized 13F reported holdings between the most recent filing and the filing 1 (3) years prior to the most recent filing. *Short Seller Trading* is calculated as the negative change in short interest / shares outstanding. Thus, a positive value of *Short Seller Trading* indicates a decrease in the short interest and vice versa. *Firm Trading* is calculated as the negative change in shares outstanding / beginning of period shares outstanding. Thus, a positive value of *Firm Trading* indicates a decrease in the shares outstanding and vice versa. All trading variables are winsorized at the 1% level. Weekly order imbalance is calculated as the average of (retail buyer initiated - retail seller initiated) / (retail buyer initiated + retail seller initiated) for the last five trading days of the month. Newey-West standard errors are utilized for the t-statistics in parentheses. The sample period is from 2006:10 to 2017:12. *, **, and *** indicate significance at the 10%, 5% and 1% respectively.

Table 8 (Continued)

	Dependent Variable: Return Residual$_{t+1}$									
	Panel A: Prior 1-Year Trading									
Retail Trading$_{t-11,t}$	0.84									2.43
	(0.08)									(0.36)
Mutual Fund Trading$_{t-11,t}$		0.25								0.60
		(0.24)								(0.69)
Bank Trading$_{t-11,t}$			-3.29							-2.43
			(-1.45)							(-1.44)
Insurance Company Trading$_{t-11,t}$				-3.56						-3.51
				(-0.95)						(-1.06)
Wealth Management Trading$_{t-11,t}$					41.46					37.84
					(1.59)					(1.39)
Hedge fund Trading$_{t-11,t}$						0.51				0.45
						(0.48)				(0.52)
Other Institutional Trading$_{t-11,t}$							-0.10			-0.27
							(-0.10)			(-0.40)
Short Seller Trading$_{t-11,t}$								0.18		-0.24
								(0.11)		(-0.22)
Firm Trading$_{t-11,t}$									0.96*	0.43
									(1.66)	(0.90)
Weekly Order Imbalance$_t$										1.08***
										(7.46)
log(Size$_t$)										0.06
										(0.91)
log(Price$_t$)										0.04
										(0.16)
Constant	-0.29	-0.35	-0.28	-0.30	-0.29	-0.35	-0.33	-0.31	-0.28	-1.25
	(-0.62)	(-0.62)	(-0.51)	(-0.54)	(-0.53)	(-0.63)	(-0.60)	(-0.57)	(-0.52)	(-1.60)
Number of Lags for Newey-West Standard Errors	12	12	12	12	12	12	12	12	12	12
No. Time Periods	122	133	133	133	133	133	133	133	133	122
N	429,951	456,386	456,386	456,386	456,386	456,386	456,386	462,230	475,605	396,833

Table 8 (Continued)

	Dependent Variable: Return Residual$_{t+1}$									
	Panel B: Prior 3-Year Trading									
Retail Trading$_{t-35,t}$	-8.77*									-5.51*
	(-1.86)									(-1.96)
Mutual Fund Trading$_{t-35,t}$		0.03								0.02
		(0.10)								(0.07)
Bank Trading$_{t-35,t}$			-0.83							0.53
			(-1.05)							(0.94)
Insurance Company Trading$_{t-35,t}$				-0.54						0.87
				(-0.39)						(1.11)
Wealth Management Trading$_{t-35,t}$					3.67					7.89
					(0.69)					(1.50)
Hedge fund Trading$_{t-35,t}$						-0.02				0.45
						(-0.04)				(0.96)
Other Institutional Trading$_{t-35,t}$							-0.36			-0.40
							(-0.90)			(-1.14)
Short Seller Trading$_{t-35,t}$								0.09		-0.35
								(0.14)		(-0.45)
Firm Trading$_{t-35,t}$									0.41**	-0.34***
									(2.02)	(-2.69)
Weekly Order Imbalance$_t$										0.94***
										(14.83)
log(Size$_t$)										0.01
										(0.32)
log(Price$_t$)										0.13*
										(1.83)
Constant	0.08	-0.38	-0.32	-0.32	-0.32	-0.33	-0.31	-0.31	-0.29	-0.37
	(0.35)	(-0.87)	(-0.70)	(-0.70)	(-0.72)	(-0.74)	(-0.68)	(-0.70)	(-0.68)	(-1.07)
Number of Lags for Newey-West Standard Errors	36	36	36	36	36	36	36	36	36	36
No. Time Periods	98	133	133	133	133	133	133	133	98	98
N	302,344	411,255	411,255	411,255	411,255	411,255	411,255	412,220	429,392	277,701