Fear or Greed? How Retail Trades Move Markets? *

Qingjie Du
The Hong Kong Polytechnic University
Email: ddvdavid.du@connect.polyu.hk

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Abstract

We document asymmetric pricing effects between the aggregate retail selling orders and aggregate retail buying orders. The long-short hedge portfolio based on retail selling orders generates about 10 bps abnormal return each day, i.e., 2% each month. However, the retail buying orders cannot predict the cross-sectional stock returns. Stocks with intensive retail selling orders continue to receive excess retail selling pressure and are associated with drying-up liquidity. The pricing effect of retail selling orders becomes stronger when the VIX is high and when market is bearish, but disappears on Fridays when the investor mood is high. We conjecture that the asymmetric attention allocation in buying and selling decisions and the asymmetric emotional impact of fear and greed together drive this asymmetric pricing effect between retail selling activities and retail buying activities.

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"Three great forces rule the world: stupidity, fear, and greed." -- Albert Einstein

"*Fear and, to a lesser extent, greed are what make money move.*" -- Michael Lewis, Liar's Poker, Page 223.

1. Introduction

Existing studies arrive conflicting conclusions on the role and performance of retail investors. The retail investors could be classified as informed traders (Kaniel, Saar, Liu, and Titman, 2012; Kelley and Tetlock, 2013; Boehmer, Jones, Zhang, and Zhang, 2020), liquidity providers (Grossman and Miller, 1988; Kaniel, Saar, and Titman, 2008; Barrot, Kaniel, and Sraer, 2016), or simply noise traders or losers (Black, 1986; Barber and Odean, 2000; Barber, Lee, Liu, and Odean, 2009). Severe data limitations of the dataset used in the previous literature are at least one reason for the mixed empirical findings (Battalio and Loughran, 2008; Barber, Odean, and Zhu, 2009; Kelley and Tetlock, 2013).[1] These limitations could lead to biased inference of the retail investors trading behaviors.

Beside, most of the exiting literature use the aggregate net order flow (i.e., net order imbalance) as the proxy of collective retail trading activities, which treats the impacts of buying activities and selling activities on stock prices equally and symmetrically.[2] However, this symmetry assumption may not be taken for granted. Brennan, Chordia, Subrahmanyam, and Tong (2012) estimate the buy- and sell-order illiquidity, and find the sell-order illiquidity shows stronger return predictability than the buy-order illiquidity. Brennan, Huh, and Subrahmanyam (2016)

[1] The potential data limitations used in previous literature include but not limited to: 1) limited sample period, 2) small stock coverage, 3) investor heterogeneity among different brokerage firms, 4) distorted order submission to NYSE, and 5) using proprietary data.

[2] To construct the order imbalance measure, researchers use the aggregate buying orders minus the aggregate selling orders, and then scale this net buying activities by some different scalers, such as total retail trading volume or total trading volume. See for example, Kaniel, Saar, and Titman (2008); Barber, Odean, and Zhu (2009); Kelley and Tetlock (2013); Boehmer, Jones, Zhang, and Zhang (2020).

document that the probability of informed trading based on bad news (but not good news) significantly affects the cost of equity. The psychology literature also shows that the emotional impact of fear and greed on investors' decision-making is asymmetric. Motivated by the above arguments, we re-examine the role and performance of retail investors by using the high-coverage and public available NYSE TAQ data, and by investigating the aggregate retail buying activities and aggregate retail selling activities separately. Our results suggest that the aggregate retail selling orders predict the cross-sectional stock returns, whereas, the aggregate retail buying orders do not. The previously documented positive relation between retail order imbalance and cross-sectional stock returns is mainly driven by the negative pricing effect from retail selling orders.[3]

Following Boehmer, Jones, Zhang, and Zhang (2020), we use the concept of "price improvement" to identify and extract the retail trading orders from the NYSE TAQ data for each individual stock at the daily level. TAQ trading data is publicly available and provides all millisecond transactions for all stocks listed on the national exchanges in the US. Due to the regulatory restrictions (e.g. Reg 606T and Reg NMS) and institutional arrangement, trading orders from the retail investors can receive price improvement, measured in small fractions of a cent per share. As a result, the trading price of retail orders are more likely to be in a format of XX.XXxx.[4] This mechanism enables researchers to identify a large proportion of the retail trading orders (Boehmer, Jones, Zhang, and Zhang, 2020). We then aggregate the retail trading orders for a

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[3] Both the informed trader explanation and liquidity provider explanation predict a positive relation between retail order imbalance and future stock returns.

[4] For example, TAQ reports a trading order for Agilent Technologies with a volume of 800 shares at a price of $41.0799 at 9:37:12.766288 on Jan 04, 2016. The market stock price should be $41.08 per share. But when the retail investor submits a buying order, the dealer will give a little discount, i.e., price improvement, to reward the retail investor for providing liquidity. The final trading price for retail orders will be recorded as $41.0799 in this case. The dollar volume is about $32,864, which will be classified as an institutional order based on the traditional trading size classification algorithm. Thus, the price improvement characteristic enables researcher to identify the retail orders more exactly.

specific stock within the same day and construct the aggregate retail order imbalance, aggregate retail buying orders, and aggregate retail selling orders, respectively.[5]

Our primary results confirm that previously documented positive relation between the aggregate retail order imbalance (i.e., net buying orders) and cross-sectional stock returns still hold in our sample. What's more surprising, we find the pricing ability of retail order imbalance mainly comes from the selling orders, rather than the buying orders. The pure aggregate buying orders do not positively predict future stock returns, but the pure aggregate selling orders significantly predict future stock returns, implying that the retail selling activities are more powerful to move the market. Even after controlling for the aggregate retail order imbalance and other well-known return predictors, the aggregate retail selling orders still provide incremental return predicting power. Specifically, the daily rebalanced long-short decile hedge portfolio based on aggregate retail selling orders produces excess returns of -10.42 bps (*t*-stat=-7.10) for equal-weighted portfolio and -9.14 bps (*t*-stat=-5.77) for value-weighted portfolio, which are about -2% per month. When we look at the aggregate retail buying orders, the corresponding excess returns become much smaller and insignificant for value-weighted portfolio. When comparing at the weekly horizon, the excess returns for the hedge portfolio based on retail selling orders become -33.07 bps (*t*-stat=-4.19) for equal-weighted portfolio and -44.85 bps (*t*-stat=-4.81) for value-weighted portfolio, which are still more than -1.3% per month. While, the excess returns for the hedging portfolio using retail buying orders flip signs, and become -8.11 bps (*t*-stat=-1.01) and -21.72 bps (*t*-stat=-1.99) for equal-weighted and value-weighted portfolios.

[5] A natural question may be that the retail trading we identified is just the counterpart of institutional trading. We provide more discussions on the retail trading data in following sections. Readers can also refer to Boehmer, Jones, Zhang, and Zhang (2020) for a comprehensive discussion.

This asymmetric return predictability still hold when we use the Fama-MacBeth (1973) regression analysis with controlling for many other return predictors. The coefficients of the aggregate retail selling orders are -2.28 (*t*-stat=-6.22) for equal weight least square (EWLS) Fama-MacBeth regression and -1.97 (*t*-stat=-3.23) for the value weight least square (VWLS) Fama-MacBeth regression.[6] On the other side, the coefficients of the retail buying orders are 0.78 (*t*-stat=2.07) and -1.50 (*t*-stat=-2.47) for EWLS and VWLS Fama-MacBeth regressions. The coefficients for the retail buying orders show much smaller magnitudes, and even flip sign when using the VWLS regression. The above results collectively provide strong support that the pricing power of aggregate retail order imbalance mainly comes from the aggregate retail selling orders.

This asymmetric pricing effect between the retail buying orders and retail selling orders raises great challenges for the existing retail trading literature. Both the informed retail investor explanation and the liquidity provision explanation have no such asymmetric predictions.[7] To explain our results, we conjecture that buying and selling decisions involve different processes. Brennan, Huh, and Subrahmanyam (2016) document that "investors who take long positions will be more concerned about informed selling than about informed buying since the former depresses the sale price whereas the latter raises it." Tetlock (2007) finds that fluctuations in negative words in the WSJ news are associated with stronger market reactions than fluctuations in positive words. Brennan, Chordia, Subrahmanyam, and Tong (2012) shows that the sell-order lambdas are

[6] To make the coefficients comparable among different characteristics, on each day, we standardize all the characteristics to N(0,1) normal distribution. Generally, the difference between the top 10% and bottom 10% sample distribution is about 3.3 times of the standard deviation. When converting the regression coefficients into excess returns of long-short portfolio, they are about 7.5 bps and 6.5 bps for equal-weighted and value-weighted hedge portfolios. The magnitude is comparable with that in the portfolio analysis.

[7] Most of the previous studies use the net order imbalance, which does not distinguish the buying orders and selling order. While we do notice some exceptions. For example, Kelley and Tetlock (2017) investigate the retail short selling activities, and find higher level of retail short selling predict lower future stock return. Boehmer, Jones, and Zhang (2008) find institutional short sellers predict stock return, but other short sellers (such as retail short sellers) do not. However, short selling is totally different from selling activities, which is much risker and is rare among retail investors. Retail investors are generally only hold long positions.

generally larger than the buy-order lambdas, suggesting that the sell-order is more powerful to affect stock price. Thus, we argue that stocks associated with intensive retail selling orders are more likely to draw retail investor attention and experience negative investor sentiment, which further drives the price to deviate from the underlying fundamentals (Shleifer and Summers, 1990). Different from institutional investors, retail investors are less sophisticated, less rational, and more emotional. The retail trading activities are more likely to be affected by investor sentiment (Lee, Shleifer, and Thaler, 1991; Barber and Odean, 2000; Barher, Lee, Liu, and Odean, 2009). Given that retail investors generally only hold long positions, the negative sentiment (or a fear sentiment) should be more influential on retail investors' trading, making the selling pressure more persistent and driving down the stock price further.

Besides the asymmetric emotional impact, investors (especially the retail investors) also suffer a heuristics bias: investors generally allocate more attention on buying decision than on selling decision due to the psychological signal that "When I sell, I'm done with it". Using a unique institutional account level trading data, Akepanidtaworn, Mascio, Imax, and Schmidt (2020) document that portfolio managers have skills to pick and buy stocks, but perform badly when selling stocks. They argue that portfolio managers spend more time and effort to dig up information when they buy the stocks, but allocate relatively less attention when selling the stocks due to the heuristics bias. In the same vein, we argue that retail investors also suffer (and even to a larger degree) this human heuristic process, which exaggerates the impact of fear sentiment. When the stock experiences intensive retail selling, the retail investors are more likely to herd to other retail investors' selling activities without careful thinking, leading to relatively concentrated and persistent retail selling orders.

To provide further support for our conjecture, we first examine the *ex ante* and *ex post* order imbalance in the 10×10 double sorted portfolios based on retail buying orders and retail selling orders. We find that the long-short hedge portfolios show consistent larger spreads in the retail selling orders than the retail buying orders, both *ex ante* and *ex post*, indicating that the retail selling orders are more concentrated in high-selling stocks. We further examine the portfolio performance and the retail trading activities around the portfolio formation day. The long-short hedge portfolio based on retail selling orders continues to receive persistent excess retail selling orders in the following one month after the portfolio formation, indicating that retail investors continue to sell the high-selling stocks. The high-selling decile group persistently underperforms by about 4 bps each day during the one-month period after the portfolio formation. However, when looking at the hedge portfolio based on retail buying orders, it only generates excess retail buying orders in the first 2 days after the portfolio formation, and only achieves positive excess return on the next day (using equal weighted portfolios). The excess retail buying orders are more transitory than the excess retail selling orders. Another point worth to mention is the decreasing average daily dollar trading volume. For the high-selling decile portfolio, the average daily trading volume before and after the portfolio formation is about $4.85M and $4.50M, or about 7% decrease, indicating that the retail selling activities are associated with liquidity drying-ups.

In case the pricing effect of retail selling orders really comes from the fearful sentiment, we expect the impact to be stronger when the market sentiment is fearful, and when the stocks are smaller and with higher volatility (i.e., hard-to-value). Our empirical results indeed support that the predicting power of retail selling orders becomes stronger when the individual stock has smaller market capitalization and has higher idiosyncratic volatility, and when the market return is below median or the VIX index is above median. On the other side, Birru (2018) and Cao, Chordia, and Zhan (2020) show that investor mood varies among the week days, when investor mood is low on Monday and high on Friday. We find that the pricing effect of retail selling orders disappears on Fridays, suggesting that high investor mood can mitigate the fearful sentiment and selling pressure.

We discuss some alternative explanations in the last part. Kaniel, Saar, and Titman (2008) argue that retail investors are compensated for providing liquidity to institutional investors. It might be that the liquidity provision is asymmetric when buying or selling stocks. We use the S&P 500 index constituents' turnover as demand shocks for certain stocks. Our results show that retail investors are more likely to buy the stocks if the stocks are added into the S&P 500 index, and to sell stocks when the stocks are excluded from the S&P 500 index. Thus, the retail investors seem to not provide liquidity to the index-tracking institutions around the S&P 500 index turnovers. Kaniel, Liu, Saar, and Titman (2012) and Boehmer, Jones, Zhang, and Zhang (2020) argue that retail investors (at least some of them) are likely to be informed investors. It could be that the retail investors know some bad news, and do not know the good news. To test this, we investigate the retail trading activities around the Earnings Announcement day (EAday). We find the retail investors simply buy stocks before the EAday, and do not distinguish positive earnings surprises or negative earnings surprises. They are just attracted by the news release and bet on the earning surprises. Formal regression tests using quarterly Fama-MacBeth regression of the post earnings announcement drift on previous retail trading activities show that both high retail selling orders and high retail buying orders in pre-announcement period predict lower post-announcement returns. However, the pre-announcement selling orders are more influential, leading to a positively relation between the retail order imbalance and post-announcement return. In summary, both the informed trading and liquidity provision explanations do not provide much explanation on the asymmetric return predictability of retail buying orders and retail selling orders.

We contribute to the retail trading literature by documenting an asymmetric pricing effect between the retail buying orders and retail selling orders. Recent research on retail investors shows that aggregate retail order imbalance can positively predict future stock returns because either the retail investors are informed or they are providing liquidity to institutions. We decompose the order imbalance, and find the pricing power mainly comes from the selling side rather than the buying side. We do not deny the argument that at least some retail investors are informed or the retail investors are compensated for providing liquidity, while the behavioral bias explanation is more plausible for the documented asymmetric pricing effects.

We conjecture that the asymmetric attention allocation in the buying and selling decisions and the asymmetric emotional impact of fear and greed sentiment together drive the trading behaviors of retail investors. Less attention with the selling decisions and more influential fearful sentiment make the retail selling more concentrated and persistent, which in turn move the price further lower. By looking at the retail investors' pure buying or pure selling activities, we provide a new angle to explain how the retail investors could move the market in the same direction as they trade.

The reminder of the paper is organized as follows. Section 2 describes the data and sample construction. Section 3 presents our main results. Section 4 examines the long term performance of retail trading activities. Section 5 explores the mechanism underlying our results. Section 6 discusses some alternative explanations. Section 7 concludes.

2. Data and sample

All our data comes from standard data sources. Our retail investor trading data comes from the NYSE trade and quote data (TAQ). We extract stock return data from the Center of Research in Security Prices (CRSP). The firm accounting data comes from Compustat/NA.

2.1. Retail trading data

In the US, most retail investors' trading orders are not directly fulfilled at the registered exchange. Rather, the retail orders are executed either by their brokerage house (i.e., internalized with broker's inventory) or by other wholesalers. Retail orders fulfilled in either of these two ways are generally reported to a FINRA Trade Reporting Facility (TRF) with an exchange code "D". In addition, these orders will generally receive a small amount of price improvement relative to the National Best Bid or Offer (NBBO) price for providing the order flow. The price improvement is usually a very small fraction of a cent, such as 0.01 cent, 0.1 cent, or 0.2 cent. The merit of this mechanism is that, the orders initiated by institutional investors generally do not receive this price improvement. Instead, the institutional orders are sent to the exchanges' dark pools. The Regulation NMS prohibits these orders in the dark pools from having subpenny limit prices. Thus, the trading prices of institutional orders are more like in round pennies. This price improvement feature enables researchers to distinguish a large proportion of retail orders and institutional orders. The trading price of retail investors is more likely to be in a format like XX.XXxx.[8] Take the previous example, TAQ reports a trading order for Agilent Technologies with a volume of 800 shares at a price of $41.0799 at 9:37:12.766288 on Jan 04, 2016. This order is more likely to be initiated by an institution in respect of the large trading size. However, the price improvement feature enables us to conclude that it is from a retail investor, and is fulfilled either by the brokerage

[8] See Boehmer, Jones, Zhang, and Zhang (2020) for a more detailed discussion. Our methodology to identify retail trading orders exactly follows the method they proposed. In their paper, they also validate this method by comparing the retail orders extracted this way with those from some proprietary trading data.

house or by a wholesaler. To further distinguish whether the retail order is initiated by a buyer or by a seller, we extract the subpenny part of the trading price. We define $\mathrm{Z} \equiv 100 \times \mathrm{mod}(\mathrm{P}, 0.01)$. By construction, Z should fall within [0,1). If Z is larger than 0 and smaller than 0.4, we define the order as a retail seller-initiated transaction. If Z is larger than 0.6, we define that transaction as retail buyer-initiated. If Z is 0 or is between 0.4 and 0.6, we define this transaction as un-identified order. This criterion is conservative, but makes the identified retail order more accurate.

After we identify all the retail trading orders, we construct three different retail trading measures: retail trading order imbalance, retail buying orders, and retail selling orders. Following Boehmer, Jones, Zhang, and Zhang (2020), we define the retail trading order imbalance for each stock *i* on each trading day *t* as:

$$OI_{bjzz(i,t)} = \frac{Total\ retail\ buying\ dollar\ volume_{i,t} - Total\ retail\ selling\ dollar\ volume_{i,t}}{Total\ retail\ buying\ dollar\ volume_{i,t} + Total\ retail\ selling\ dollar\ volume_{i,t}} \quad (1)$$

To construct the aggregate retail buying orders and retail selling orders, we define the corresponding retail trading measures for stock *i* on trading day *t* as:

$$R_{buy(i,t)} = \frac{Total\ retail\ buying\ dollar\ volume_{i,t}}{Total\ dollar\ trading\ volume_{i,t}} \quad (2)$$

$$R_{sel(i,t)} = \frac{Total\ retail\ selling\ dollar\ orders_{i,t}}{Total\ dollar\ trading\ volume_{i,t}} \quad (3)$$

2.2. Discussion on the retail trading measures

The retail trading data extracted from this method has some advantages. First, in earlier studies, trading orders below a certain trade size (e.g. $20,000) will be classified as small retail trading activities (Lee and Radhakrishna, 2000). While this method becomes inaccurate after the adoption of computer algorithms in trading. Campbell, Ramadorai, and Schwartz (2009) document that trading orders below $2,000 are more likely to come from institutions. Second, different with previous proprietary datasets used in retail investor literature, this TAQ data has the most comprehensive stock coverage with relative longer data period. Researchers can extract the retail trading orders for almost all individual stocks. Second, different with the NYSE data used in Kaniel, Saar, and Titman (2008) and other studies (which do not differentiate market order and limit order), the retail orders identified from our method only contain market order. The distinction between market order and limit order may bias the interpretation (Barber, Odean, and Zhu, 2009; Kelley and Tetlock, 2013). Market orders are more suitable for the study of investor sentiment.

A natural question might be that the retail trading is just the counterpart of the institutional trading. While, different institutions show huge heterogeneity. For example, hedge fund is very different from mutual fund. In this sense, the retail trading may show more commonality. Further, our retail trading measure only contains the market order. Limit order is excluded from the analysis. Thus our measures mainly reflect the active trading behaviors from a fraction of the retail investors. Lastly, a considerable institutional trading is executed in the format of cross-trading - transactions within the same fund family – that are not exposed to an external marketplace (Chan, Conrad, Hu, and Wahal, 2018; Eisele, Nefedova, Parise, and Peijnenburg, 2020).

Besides the data source, the retail trading measure constructions are also different from previous literature. In Boehmer, Jones, Zhang, and Zhang (2020), they use the total retail trading volume as the scaler. This measure is equivalent to the ratio of aggregate retail buying volume and aggregate retail selling volume.[9] This construction method combines the buying activities and selling activities together, and cannot distinguish which component is more important. Besides, the order imbalance measure also ignores the impact of the absolute level of retail trading activities. Large stocks generally are less affected by the retail investors than the small stocks. To construct our retail buying orders and retail selling orders, we cannot use the total retail trading volume as

[9] See the formula for details: $\frac{X-Y}{X+Y}=\frac{\frac{X}{Y}-1}{\frac{X}{Y}+1}\rightarrow\frac{X}{Y}$; and $\frac{X}{X+Y}=\frac{\frac{X}{Y}}{\frac{X}{Y}+1}\rightarrow\frac{X}{Y}$; and $\frac{Y}{X+Y}=\frac{1}{\frac{X}{Y}+1}\rightarrow-\frac{X}{Y}$

the scaler because it will make both measures be equivalent to the ratio of retail buying orders and retail selling orders (see footnote 9). Thus, we use the total daily trading volume as the scaler to construct the retail buying measure and retail selling measure.

Kaniel, Saar, and Titman (2008) construct the net individual trading by subtracting the individual selling volume from the individual buying volume, and standardize the measure by the average daily dollar trading volume in previous one year. Since individual investors trade more frequently, using the one-year average trading volume may ignore some timely trends that may affect the trading activities. The total market capitalization might be another potential scaler. But for some stocks, a high proportion of the total shares may be held by passive mutual funds, which do not trade frequently. Thus using the total market capitalization is not a best scaler.

In summary, when constructing the retail order imbalance measure, we follow Boehmer, Jones, Zhang, and Zhang (2020), i.e., use the ratio of the buying orders and selling orders. However, when constructing the aggregate retail buying orders or the aggregate retail selling orders, we use the total daily trading volume as our main scaler. In the online appendix, we also show some robustness analysis using different retail measures.

2.3. Control variables

We follow the existing literature to construct stock characteristics that can predict future stock returns, which include market capitalization (Mep), market beta (Beta252), book-to-market ratio (B/M), asset growth (TAG), operating profitability (OP), past one-year stock return from day *t*-252 to day *t*−21 (MOM252), past 21 trading day return (STR21), and past one trading day return (Return *t*). We collect the number of analyst coverage (Analysts) data and the analyst forecasting dispersion (Dispersion) from I/B/E/S and calculate institutional ownership (IO%) from the Thomson Reuters 13F database. We also construct the following measures that proxy for lottery-type features: idiosyncratic volatility (IVOL21) (Ang, Hodrick, Xing, and Zhang, 2006) and maximum daily return (MAX21) (Bali, Cakici, and Whitelaw, 2011). We estimate the market friction and illiquidity measures using average daily bid-ask spread (Spread) and Amihud illiquidity (ILLIQ). We winsorize all continuous variables at the 1% and 99% levels to remove the influence of outliers. The full details of variable construction are presented in Table 1.

After we collect all the data, we merge the retail trading data with the daily stock returns and accounting data from CRSP and Compustat, respectively. We only include common stocks (stock share code 10 or 11) listed on NYSE, AMEX, and NASDAQ. To minimize market microstructure biases associated with extreme illiquid stocks, we remove lowprice stocks with stock price less than $1 in previous trading day (Kelley and Tetlock, 2017; Boehmer, Jones, Zhang, and Zhang, 2020). To mitigate the noisy in the retail trading measures, we limit our analysis to stocks with a minimum of two retail trading orders (one buying order and one selling order) on each day.[10] We also exclude stocks with retail buying volume or selling volume greater than the total daily trading volume.[11] Our final sample contains about 4.9 million stock-day observations, covering 1762 trading days from 2010 to 2016.

3. Empirical results

We report our main results in this section. We first present the summary statistics of stock characteristics within sub-groups formed by different retail trading measures. Next, we report the daily rebalanced portfolio analysis results. We also show the 10×10 double sorted portfolios'

[10] Barher, Odean, and Zhu (2009) require the stocks to have at least 10 small trades at the weekly frequency. Kelley and Tetlock (2013) require the stocks to have at least 5 orders each day. Our results are similar when using different cut points or using no cut point.

[11] Our results are materially the same if we (1) exclude stocks with price lower than $5 in the previous day, (2) exclude stocks with market cap below the 20th percentile of NYSE stocks, and (3) include stocks with only one retail trading order identified.

returns based on retail buying orders and retail selling orders, and present the Fama-MacBeth (1973) regression results with controlling for many other stock characteristics in the last.

3.1. Summary statistics of retail trading activities and stock characteristics

We present the sample descriptive summary statistics in Table 1. Panel A shows the distribution of the retail trading activities during our sample period. Panel B, C, and D show the time-series average of the stocks characteristics within different sub-groups formed by retail selling activities, retail buying activities, and retail order imbalance. Panel E presents the time-series average of the correlation matrix between different variables.

[Insert Table 1 here]

The result in Panel A shows that the average daily trading volume for each individual stock is about $38.1 million from 6338 trading orders, indicating that the average dollar trading volume is only a bit higher than $6000 for each order. When we look at the retail trading orders, the average dollar volume is about $2.3 million, or 6% of the total trading volume. The average retail trading amount is about $10,135 per order, which is larger than the average dollar amount of all orders. This result is consistent with the usage of computer algorithms after the early 2000s that enables the institutions to "slice and dice" the large institutional parent orders into a sequence of small child orders. Campbell, Ramadorai, and Schwartz (2009) also document that small trades are more likely to come from institutional investors in recent period. When comparing the retail buying activities and the retail selling activities, the total dollar volume is very close. The retail selling volume ($1.16M) is about 1% higher than the retail buying volume ($1.15M). While, when looking at the percentage values, the average retail selling (buying) volume becomes 4.28% (4.11%), with a difference of more than 4%. The difference in the dollar volume and the percentage volume provides the first clue that retail selling orders are more concentrated in low trading volume stocks (not necessary small stocks).[12] While overall, the retail trading only account for a small proportion in the US market.

Panel B to D report the time-series averages of stock characteristics in different sub-groups formed on the retail selling orders, retail buying orders, and retail order imbalance, respectively. Comparing the results in Column (10) in Panel B and Panel C, we find some similarity of the stocks associated with intensive retail selling orders or retail buying orders. For example, both stocks have small market capitalization ($0.36B for selling-intense stocks, and $0.5B for buying-intense stocks), higher book to market equity (0.85 VS 0.84), low profitability (0.03 VS 0.03), low institutional holding, fewer analyst following, and higher analyst forecast dispersion. Both of them show lottery-type characteristics, including higher max daily return in previous 21 trading days, higher idiosyncratic volatility, and higher bid-ask spread. They perform well in the previous 21 days, but are the losers in previous 252 days. When looking at Panel D, the results in Column (-10) and Column (10) also confirm the above patterns, but the degree is attenuated. We also note that the extreme sold (or bought) stocks also attract large buying (or selling) orders from retail investors. The main implication is that retail investors' trading focuses on some certain stocks, but the expected stock returns disperse greatly among the retail investors, which triggers both the large buying and large selling. This pattern is also consistent with Kumar and Lee (2006) that documents retail investors trade within their habit.

One interesting pattern worth to note is that, in Panel B and Panel C, when comparing the portfolio return on the formation day (Return *t*) in Column (9) and (10), both the best-performance

[12] On average, the retail buying volume is close to the retail selling volume, but the percentage difference becomes larger, i.e. selling is more concentrated on low trading volume stocks. For example, stock A and B have the same market size, and the trading volumes are $100 and $1000. In stock A, the retail buy is $1, and sell is $9; while in stock B, the retail buy is $9 and retail sell is $1. When using the dollar amount, the average volumes are all $5, while when comparing the percentage, the buying volume is (1/100+9/1000)/2≈1%; the selling volume is (9/100+1/1000)≈4.5%.

stocks and worst-performance stocks are traded (either buy or sell) heavily by retail investors. The total retail trading volume is more than 25% in Column (10). The results are somewhat different as in Kaniel, Saar, and Titman (2008) which find that retail investors tend to be contrarian. Rather, our results are more consistent with the argument that retail investors are attracted by exciting news, and they are gambling in the market.

Panel E reports the time-series average of the Spearman correlation and Pearson correlation among different variables. The correlation between retail buying and retail selling is higher than 0.5, indicating that some certain type of stocks attract the retail investors' attention. On average, both the retail buying and retail selling show low correlation with the previous day return and previous 21 day return, but high correlation with the max daily return in previous 21 days, suggesting that retail investors are simply gambling in the market.

3.2. Dissecting retail trading activities: Portfolio sorts

3.2.1. Portfolio sorts using retail buying and selling measures separately

On each day, we sort stocks into deciles either based on the aggregate retail buying orders or the aggregate retail selling orders, and calculate realized returns of each portfolio in the following trading day. We then calculate the returns to a zero-cost portfolio that is the difference in returns between the top and bottom decile portfolios. We report the average portfolio excess returns (raw return over the risk-free rate) and alphas based on the CAPM, Fama-French three-factor, and Carhart four-factor models using both equal- and value-weighted approaches. We also estimate the excess returns or alphas using the second extreme portfolios (i.e., the 2^{nd} and 9^{th} portfolios).

[Insert Table 2 here]

Table 2 Panel A presents the portfolio returns sorted by the aggregate retail selling orders. Stocks associated with high retail selling activities show significant lower future returns. The long-short portfolio generates an average daily return of −10.42‱ (t-stat = −7.10) and −9.14‱ (t-stat = −5.77) for equal-weighted and value-weighted portfolio returns respectively, which are more than −2% per month. The portfolio alphas using the CAPM model, the three- and four-factor models produce similar patterns. The equal-weighted alphas are −9.52‱ (t-stat = −6.01), −9.58‱ (t-stat = −6.11), and −9.50‱ (t-stat = −6.06), respectively. The value-weighted alphas are a bit smaller, but still higher than 9‱. We also show the long-short portfolio using the second extreme decile portfolios, and all the results are still significantly negative. A robust return pattern emerges across these specifications. Moreover, the high-selling portfolios exhibit significantly negative risk-adjusted average returns, and the low-selling portfolios exhibit significantly positive risk-adjusted average returns. This suggests that the negative pricing effect of retail selling orders is both due to the underperformance of high-selling stocks and due to the outperformance of low-selling stocks.

In Panel B, we repeat the portfolio analysis results using the aggregate retail buying orders. Surprisingly, the return predictability of aggregate retail buying orders are much weaker. Value-weighted portfolios do not generate any significant results. Although the equal-weighted portfolio generate significant positive hedge returns using the extreme decile portfolios, the long-short hedge returns flip signs when using the second extreme decile portfolios. Besides, the daily hedge return and factor-adjusted alphas are much smaller than those based on the aggregate retail selling orders.

In summary, the results show that there exist distinctive differences in the pricing effects of aggregate retail selling orders and retail buying orders. The aggregate retail selling orders are much powerful to move the stock price.

3.2.2. 10×10 Portfolio sorts using retail buying and selling measures

To further compare the pricing effects of retail buying activities and retail selling activities, we sort stocks into 10×10 portfolios based on both the aggregate retail buying orders and the aggregate retail selling orders. We then calculate realized returns of each portfolio in the following trading day. Specifically, in Table 3 Panel A, we first sort all the stocks into decile portfolios by the retail buying orders, and then further sort stocks in each decile portfolio into finer decile portfolios by the retail selling orders. This method ensures that all the individual stocks in each decile portfolio based on retail selling orders have similar retail buying orders. We then calculate the realized long-short portfolio returns in the next trading day. In Panel B, we reverse the sorting process by first sorting stocks by the retail selling orders, and then by the retail buying orders.

[Insert Table 3 here]

Table 3 presents our analysis results. To save space, we only report the results of 1st, 2nd, 5th, 6th, 9th, and 10th portfolios. Results in Panel A show that when the stocks are associated with similar buying orders, different levels of retail selling orders still predict significant cross-sectional difference in the stocks' realized returns. The pricing effect of retail selling orders are more significant when the stocks have higher retail buying orders (i.e., the stocks are heavily traded by retail investors). Specifically, the long-short hedge portfolio returns for stocks with highest retail buying orders are −16.65‱ (t-stat = −5.30), and −14.79‱ (t-stat = −4.94) for equal-weighted and value-weighted, respectively. The magnitudes are almost twice as for the stocks with lowest retail buying orders.

In Panel B, we do similar analysis, but we first sort stocks by the retail selling orders, and then by the retail buying orders. For the equal-weighted 10×10 portfolios, we find similar results as in Panel A. But for the value-weighted portfolios, only the 2nd hedge portfolio generates significant results, indicating that when the stocks are associated with similar retail selling orders, the retail buying orders do not affect the future stock prices.

Combine the results in both Panel A and Panel B, we conclude that the retail selling orders still negatively predict future stock return even after we control for the retail buying orders, but not the other way.

3.3. Dissecting retail trading activities: Fama-MacBeth regression

The portfolio sorting results show strong evidence that there exists distinctive pricing effects of retail selling orders and retail buying orders. However, other characteristics or a combination of characteristics may explain the negative retail selling premium (Fama and French, 2008). To investigate the marginal power of retail selling on expected returns, we estimate cross-sectional Fama-MacBeth regressions. The baseline regression includes controls for total order imbalance, stock size, market beta, book to market equity, operating profitability, asset growth rate, momentum, short-term reversals, maximum daily stock return, idiosyncratic volatility, and stock turnover rates. We estimate both equal-weighted least squares (EWLS) regressions and value-weighted least squares (VWLS) regressions. To compare coefficient estimates across different specifications, we normalize all variables on the same day to have zero mean and standard deviation of one. Table 4 reports the time-series averages of the coefficient estimates for the 1762-trading-day period between 2010 and 2016. The t-statistics are adjusted following Newey and West (1987) with up to 12 lags.

[Insert Table 4 here]

Panel A and Panel B report the EWLS and VWLS results, respectively. In column (1) to (3), we test the retail trading measures one by one separately, and in column (4) to (6), we test the combination of them. In Panel A, column (1) to (3), the retail selling orders has the largest coefficients (coeff.=-3.39, t-stat.=-10.45) among the three retail trading measures, suggesting the retail selling orders has the strongest pricing power. Comparing the results in column (5) and (6), the retail buying orders almost lose return prediction power after controlling for the retail order imbalance constructed following Boehmer, Jones, Zhang, and Zhang (2020), i.e., the ratio of retail buying volume to retail selling volume. But the retail selling volume still provides incremental return predicting power (coeff.=-2.28, t-stat.=-6.22).

The results in Panel B are more obvious. When we test the aggregate retail buying orders separately in column (2), the coefficient is not significant (coeff.=-0.15, *t*-stat=-0.29). The coefficient of retail buying orders in column (6) even becomes negative and significant (coeff.=-1.41, t-stat.=-2.23) after we control for the retail order imbalance measure. For the retail selling measures, the coefficients are always significant negative at the 1% levels. After controlling for the retail order imbalance, the coefficient still has large magnitude (coeff.=-1.97, *t*-stat=-3.23), which is equivalent to about 6.5 bps using long-short decile hedge portfolios.

In summary, the portfolio analysis results and the Fama-MacBeth regression results together support that the retail selling activities have stronger pricing effects than the retail buying activities, and the pricing power of retail order imbalance documented in previous literature mainly comes from the selling side.

4. Long term analysis

We conduct additional tests to examine the long-term performance of the retail selling orders and retail buying orders. The results in this section make the trading strategy more flexible and help to address the concern on the transaction fee.

4.1. Weekly rebalanced portfolio analysis

To construct the weekly retail buying orders and retail selling orders, we aggregate all the retail orders within each week, and construction the weekly measure as the same in equation (1) to equation (3). At the end of each week, we sort stocks into decile portfolio, and estimate the realized portfolio return in the following week.

[Insert Table 5 here]

Table 5 reports the results. To save space, we only report the results for the 1^{st}, 2^{nd}, 5^{th}, 6^{th}, 9^{th}, and 10^{th} decile portfolio. Panel A and Panel B present the returns for retail selling orders and retail buying orders, respectively. In Panel A, the long-short hedge returns and alphas for portfolio based on retail selling order range from -29.42‱ (t-stat.=-3.73) to -46.50‱ (t-stat.=-4.88), which are more than -1% each month. While the results in Panel B show that the weekly retail buying orders are negatively associated with future stock returns, and the value-weighted results are marginal significant. Combine the results, we conclude that the transaction costs do not affect the asymmetric pricing power of the aggregate retail selling orders and retail buying orders. What's more, the relation between retail buying orders and future stock returns becomes negative, i.e. stocks associated with intense retail buying orders perform worse in future.

4.2. Buy and hold return

We also test the persistent of the pricing effect from retail selling orders and retail buying orders. Boehmer, Jones, Zhang, and Zhang (2020) investigate the retail order imbalance using the weekly rebalanced portfolios, and they find the retail order imbalance order can predict future stock returns up to 12 weeks, i.e. once we establish the portfolio, we can hold it without rebalance up to 12 weeks. We do a similar analysis, but use the retail selling orders and retail buying orders separately. On each trading day t, we establish the portfolio based on one of the retail trading measures, and hold the portfolio constant for the following 21 days. We then compare the 21-day buy and hold return for the decile portfolios. In the analysis, the transaction cost should be a minor issue since we do not rebalance the portfolio for the following 21 days.

[Insert Table 6 here]

Table 6 presents the results. Panel A shows the results based on the retail selling orders, and Panel B shows the results based on the retail buying orders. The long-short returns and alphas of the portfolio based on retail selling orders range from -0.77% (t-stat.=-4.91) to -1.18% (t-stat.=-5.86), which is still comparable to that based on daily portfolios or weekly portfolios.

In Panel B, we find similar pattern as that in the weekly portfolio analysis. All the long-short returns and alphas of the hedge portfolio based on retail buying orders flip signs, i.e. stocks with high retail buying orders underperform in the long run. What's more, the results become significant at the 1% level. We also note that the absolute magnitudes of the hedge returns based on buying orders are much smaller than those based on the selling orders, which helps to reconcile the positive relation between retail order imbalance and future stock returns.

Combine the results in Table 5 and Table 7, we conclude the retail selling orders negatively predict stock return even in the longer term. But the retail buying orders lose return predicting powers, and even flip signs in longer term. The transaction cost will not affect the asymmetric pricing impact.

5. Mechanism test

In the previous analysis, we document a strong and robust asymmetric pricing effect between aggregate retail selling orders and retail buying orders. We explore some possible channels that could explain the asymmetric relation in this part. We first compare the *ex ante* and *ex post* retail order imbalance in the sub groups based on retail selling orders or retail buying order. We also track the portfolio performance and retail trading activities around the portfolio formation day. Lastly, we examine the heterogeneous pricing power in different subgroups.

5.1. Concentrated selling and dispersed buying

The summary statistic in Table 1 Panel A provide first evidence that the retail selling orders are more concentrated on low trading volume stocks as the average percentage of retail selling orders are much higher than the retail buying order. This also implies that the spread of retail selling orders should be larger than that of the retail buying order. We formally test this idea by comparing the retail selling order spread and retail buying order spread after we control for the retail buying activities or retail selling activities. On each day, we form the 10×10 double sorted portfolios as we do in Table 3, i.e. either first sorting stocks by retail buying order and then by retail selling orders or first sorting stocks by retail selling orders and then by retail buying orders. Instead of reporting the portfolio return, we report the average net retail buying orders in each sub-group on both the portfolio formation day and the next day after portfolio formation.

[Insert Table 7 here]

Table 7 presents the results. In Panel A, we first sort stocks into decile portfolios, and then further sort stocks in each portfolio into finer decile portfolios. In Panel B, we reverse the sorting sequence. When we control for the aggregate retail buying orders (Panel A), the average retail selling order spread in the high-selling portfolios and low-selling portfolios is about 12.50% *ex ante* (ranked from 7.47% to 22.09%) and 1.01% *ex post* (ranked from 0.75% to 1.40%). When we control for the aggregate retail selling orders (Panel B), the average retail buying order spread is 11.99% *ex ante* (ranked from 6.83% to 22.83%) and 0.56% *ex post* (ranked from 0.40% to 0.70%). The spread of the selling orders is about 0.5% larger than the spread of retail buying orders both *ex ante* and *ex post*. This pattern helps to explain why the retail selling orders are more powerful to move the market.

5.2. Persistent selling and transitory buying

To further explore the retail trading activities and stock performance around the portfolio formation day, we first track the portfolio performance in the two-week-before and four-week-after the portfolio formation. We plot the daily portfolio performance in Figure 1 to Figure 3.

[Insert Figure 1 to Figure 3 here]

Figure 1 shows the daily portfolio returns of the decile portfolios based on the aggregate retail selling measures. On day 0, we rank all the stocks into decile portfolios by the aggregate retail selling orders on that day. We find the high-selling decile portfolio perform worst on day 0, but perform best during the previous 9 trading days except the portfolio formation day (i.e., day 0). When we look at the post-formation performance, we find the high-selling portfolio underperform by about 10 bps in the following trading day, and continues to underperform by about 5 bps each day starting from day 2 until day 21. The pattern is strongly persistent.

The results in Figure 2 and Figure 3 show different patterns. In Figure 2, the decile portfolios based on aggregate retail buying orders, we do not find any persistent patterns. The long-short hedge returns are close to zero in the first several days (except day 1) and then becomes negative in longer window. Figure 3 shows the decile portfolios based on the retail order imbalance (the ratio of retail buying orders to retail selling orders). All the hedge returns are positive, but after one week of the portfolio formation, the magnitudes become much smaller and close to zero.

[Insert Table 8 here]

We present the formal comparison of the portfolio performance in Table 8.To save space, we only report the results for the 1^{st} and 10^{th} decile groups and the long-short hedge portfolio. For each decile group, we report the average daily dollar trading volume, aggregate retail buying orders and selling orders, the difference in the buying and selling orders, and the average daily portfolio return. Panel A shows the results for retail selling orders, and Panel B shows the results for retail buying orders. The long-short portfolio returns in both panels show similar pattern as in Figure 1 and Figure 2. For the retail selling orders, all the daily returns before the portfolio formation are positive, indicating the high-selling stocks perform well in the pre-formation period. While on the formation day, the pattern reverses. The high-selling stocks experience a dramatic drop in the stock price, with the average return of -19.51 bps (*t*-stat.=-10.82). The trend continues after the portfolio formation, with the first day return of -10.42 bps (*t*-stat.=-7.10), and then drops to about 4 bps each day for the next 20 days. Interestingly, the high-selling stocks have already experienced excess selling pressure before the portfolio formation, ranging from 0.24% to 0.49% each day, and continues to receive excess selling orders in the post-formation period, ranging from 0.38% to 0.65% each day. It seems the extreme selling orders (7.22%) on the formation day trigger the crash of the high-selling stocks. A last point to mention is the daily trading volume. Before the portfolio formation, the 10^{th} decile group (high-selling group) have a daily average dollar trading volume of \$4.85M, and the volume drops to \$4.50M in the post-formation period, indicating that the high-selling stocks are also associated with drying-up liquidity.

When we look at the decile portfolios formed by the aggregate retail buying orders, we do not find any persistent patterns. The long-short portfolio does not show positive return except the three-day window around the portfolio formation. Although the high-buying decile group receive excess buying order before the portfolio formation, this trend does not hold since the 3^{rd} day in the post-formation period. The trading volume is much larger in the high-selling decile than that in the high-selling decile.

Overall, the results in Table 8 suggest that the retail selling activities are more concentrated and more persistent than the retail buying activities. Besides, the retail selling activities are also associated with drying-up liquidity. These evidences help to explain the asymmetric pricing effects of the retail buying activities and retail selling activities.

5.3. Investor sentiment and stock characteristics

The above analysis shows that the concentrated and persistent retail selling activities move the market to the same direction as the retail investors trade. To further explain the phenomena, we conjecture that the asymmetric emotional impact of fear and greed sentiment drives this result. To proxy for the potential sentiment effects, we use two firm-level measures and two macro-level measures. Small firms have relatively more asymmetric information environment, thus are more likely to be affect by the fear sentiment. Similarly, stocks with high idiosyncratic volatility are more uncertain, and more likely to be affected by the fear sentiment. For the macro-level environment, we use the VIX index and market return. Specifically, we define trading days with VIX above the period median as high VIX period, and trading days with market return lower than the period median as low MKT period. The retail selling activities should become more powerful on the high VIX period and bearish market period. We then run the Fama-MacBeth regression including the interaction terms.

[Insert Table 9 here]

Table 9 presents the results. Panel A and Panel B show the EWLS results and VWLS results. We find that the pricing effect of retail selling activities becomes stronger when the stocks are small and with high idiosyncratic volatility. The effects are also stronger when the market return is lower and VIX index is higher. The negative pricing effects are almost doubled. These results support that retail investors' trading are driven more by the fear sentiment.

5.4. Investor mood: weekday effects

A prominent phenomena in the psychology literature is that human mood increases from Thursday to Friday, while decreases on Monday. People/investors become more optimistic of future prospects when they are in good mood than when they are in bad mood (Wright and Bower, 1992). Birru (2018) shows that stock market anomalies whose speculative leg is the short leg experience the highest returns on Monday, and becomes very weak or insignificant on Friday. Cao, Chorida, and Zhan (2020) also document that the IVol effect mainly occurs on Monday, and even reverses on Friday. We conduct similar tests to check whether the investor mood affect the retail selling orders' pricing ability by investigating the weekday effects. At the end of each week, we estimate the average retail selling measures for each stock for the past one week, and rank all the stocks into decile portfolios. We then hold these decile portfolios for one week, and report the daily portfolio returns on each day in the following week.

[Insert Table 10 here]

Table 10 presents the results. Panel A and Panel B show the EW and VW results. We find that the pricing effect of retail selling activities becomes insignificant on Fridays, as the long-short returns or alphas becomes insignificant or flip signs. The negative relation between retail selling orders and future stock return hold from Monday to Thursday, with Tuesday and Thursday show the strongest effects. Taken together, the high investor mood mitigates the fearful sentiment associated with intensive retail selling activities.

6. Alternative explanation

We briefly discuss some alternative explanations in this section, including asymmetric liquidity provision, asymmetric informed trading on good or bad information, and some other explanations.

6.1. Asymmetric liquidity provision

Kaniel, Saar, and Titman (2008) argue that retail investors are compensated by providing liquidity to the institutional investors, thus the retail order imbalance could positively predict future stock return. It might be that the institutions' buying and selling activities are different, leading to asymmetric liquidity provisions from the retail investors. In this section, we investigate the retail trading activities around the S&P 500 index constituents' turnover. There exist large amount of index-tracking funds that follow the index constituents. Once a stock is added into the S&P 500 index, it will attract a lot of institutional buying activities. Practically, the S&P index change will be announced one month before the real effective day, thus we focus on a period one-week before the accouchement day and four-week after the effective inclusion day for each S&P 500 index addition or deletion, i.e., (-25, 20) window around the effective turnover day.

[Insert Table 11 here]

We present the results in Table 11. Panel A reports the results around index addition, and Panel B reports the results around index deletion. We report the average dollar trading volume, retail buying orders, retail selling orders, the difference between retail buying and retail selling, and the stock performance.

Firstly, we note that both the retail buying and selling activities drop greatly during the three-day window (-2, 0) before the effective day. Since we use the total trading volume as the scaler, this dramatic drop is more likely to be driven by the increased institutional trading volume. Except this point, we do not find any significant pattern during this 9-week period. The net retail buying orders are positive in Panel A, and are negative in Panel B, suggesting that the retail investors are also buying the stock added into the index, and selling the stocks that are deleted from the index. The market adjusted stock returns for the added or deleted stocks are insignificant from 0 either. These results suggest that retail investors are not providing liquidity to the institutional investors, at least not during the S&P 500 index addition or deletion window. While we admit that, due to the low-frequency of S&P 500 index turnover, our tests in this part may not be so informative.

6.2. Asymmetric informed trading

Kaniel, Liu, Saar, and Titman (2012) investigate the retail trading activities around the firms' Earnings Announcement days (EA days), and argue the retail investors trade as they are informed. Thus, it might be that the retail investors perform asymmetrically for the good news stocks and bad news stocks, i.e., retail investors know bad news but do not know good news. Although this explanation is not plausible, we do a similar analysis as for the S&P 500 index turnover to investigate the retail trading activities around the EA days.

[Insert Table 12 here]

Table 12 presents our results. In each quarter, we estimate the standardized earnings surprises (SUEs) for each stocks, and rank the stocks into quintile groups based on their SUE. Panel A to C report the results for the extreme positive SUE quintile (Q5), moderate SUE quintile (Q3), and extreme negative SUE quintile (Q1). For each quintile, we report the average daily trading volume, retail buying orders, retail selling orders, the difference between retail buying and selling, and the average stock returns.

We find that just before the EA days, retail investors buy the stocks for all stocks. The net buying for the three quintile groups are 0.52% (*t*-stat.=8.86), 0.26% (*t*-stat.=8.59), and 0.27% (*t*-stat.=3.83) for Q5, Q3, and Q1 respectively. It seems the retail investors do not distinguish whether the stock can beat the forecast, rather they are attracted by the EA news, and simply bet on the earnings announcement. After the earnings news are released, the retail investors start to sell the stocks, as the net buying for the three groups become -0.41% (*t*-stat.=-10.37), -0.15% (*t*-stat.=-6.68), and -0.42% (*t*-stat.=-6.30). We also show that the Post Earnings Announcement Drift (PEAD) still exist in recent period, but the drift becomes much weaker after the first week.

To conduct a formal regression test on the informed trading explanation, we estimate both the cumulative stock returns (CAR) using different periods after the EA day and retail trading activities in the pre-announcement period. Then we conduct a quarterly Fama-MacBeth regression, i.e. we regress CARs among different horizon on the retail selling, retail buying, and retail order imbalance measures in the pre-announcement period quarter by quarter, and report the average coefficients. We do the regression separately for different retail measures with all the control variables as in Table 4, but report the coefficients on retail trading measures into one table, and omit the coefficients of control variables for brevity.

[Insert Table 13 here]

Table 13 reports the results. Panel A to Panel C reports the results based on retail trading measures among different period before the EA days. In all three panels, we find similar and consistent patterns. Both the retail selling measures and retail buying measures negatively predict future CARs after the earnings announcement, but the negative effect is stronger, leading to a positive relation between retail order imbalance and future CARs. Following the informed trading, our results could suggest that retail investors only know bad news, but are cheated by the good news as the retail buying activities negatively predict future CARs, which is not convincing.

To sum up, our results are similar as in Kaniel, Liu, Saar, and Titman (2012), which also document that retail investors are attracted by the EA events and start to buy the stocks before the

EA days. But our results suggest the retail investors do not distinguish the good news stocks and bad news stocks. They just bet on the news. We do not find any evidence to support the argument that there exist asymmetric informed trading patterns among the retail investors.

6.3. Other possible explanations

There may still exist some alternative explanations to explain the asymmetric pricing effect between retail buying activities and retail selling activities. For example, the litigation enforcement against insider trading on good news and bad news may be different. It might be harder to detect the inside trading on bad news, thus the retail investors could acquire some inside information and start to sell the stocks. Another possible explanation may be that the institutions buy and sell stocks in asymmetric ways. When the institutions buy stocks, they "slice and dice" the block orders to hide their trading directions, but when the institutions sell the stocks, they may become less patient to do so. Due to the less trading constrain or reputation constrain of retail investors, they can even ride on the institutions and trade much faster.

While, we cannot exclude these possibilities, the asymmetric emotional impact of fear and greed sentiment together with the asymmetric attention allocation are more plausible to explain our results. The drying-up liquidity associated with the retail selling activities also exaggerates the fearful sentiment, which makes the retail selling activities more powerful to move the market.

7. Conclusion

In this paper, we use the unique feature that retail orders will receive price improvement in the US equity market to identify retail investor trading activities and investigate the impact of their trading orders. We find consistent results that the aggregate retail trading order imbalance could positively predict future stock returns. We further decompose the retail order imbalance into retail buying orders and retail selling orders, and we find the pricing effect of retail order imbalance mainly comes from the selling side. Using the pure retail selling orders, the daily rebalanced long-short portfolio could generate more than 10 bps abnormal returns each day. Moreover, this negative pricing effect is still strong and persistent in longer terms. After considering the transaction cost, the trading strategy based on the pure retail selling orders still generate more than 1% abnormal return each month. While when we do the same analysis using the retail buying orders, we do not find any meaningful results. The retail buying orders do not positively predict stock return in short term, and the relation even becomes negative in the longer periods.

We explore several possible explanations for the asymmetric pricing effect between retail buying orders and retail selling orders, and conjecture that the asymmetric impact of fear emotion and greed emotion together with the asymmetric attention allocation drive this asymmetric pricing effect. Retail investors are more likely to be affected by the fear emotion, and they also suffer from the cognitive biases (i.e., allocate more attention on the buying decision and less attention on selling decision). These two factors combined makes the retail selling orders more concentrated and more persistent, which move the stock price in the same direction as the retail investor trade.

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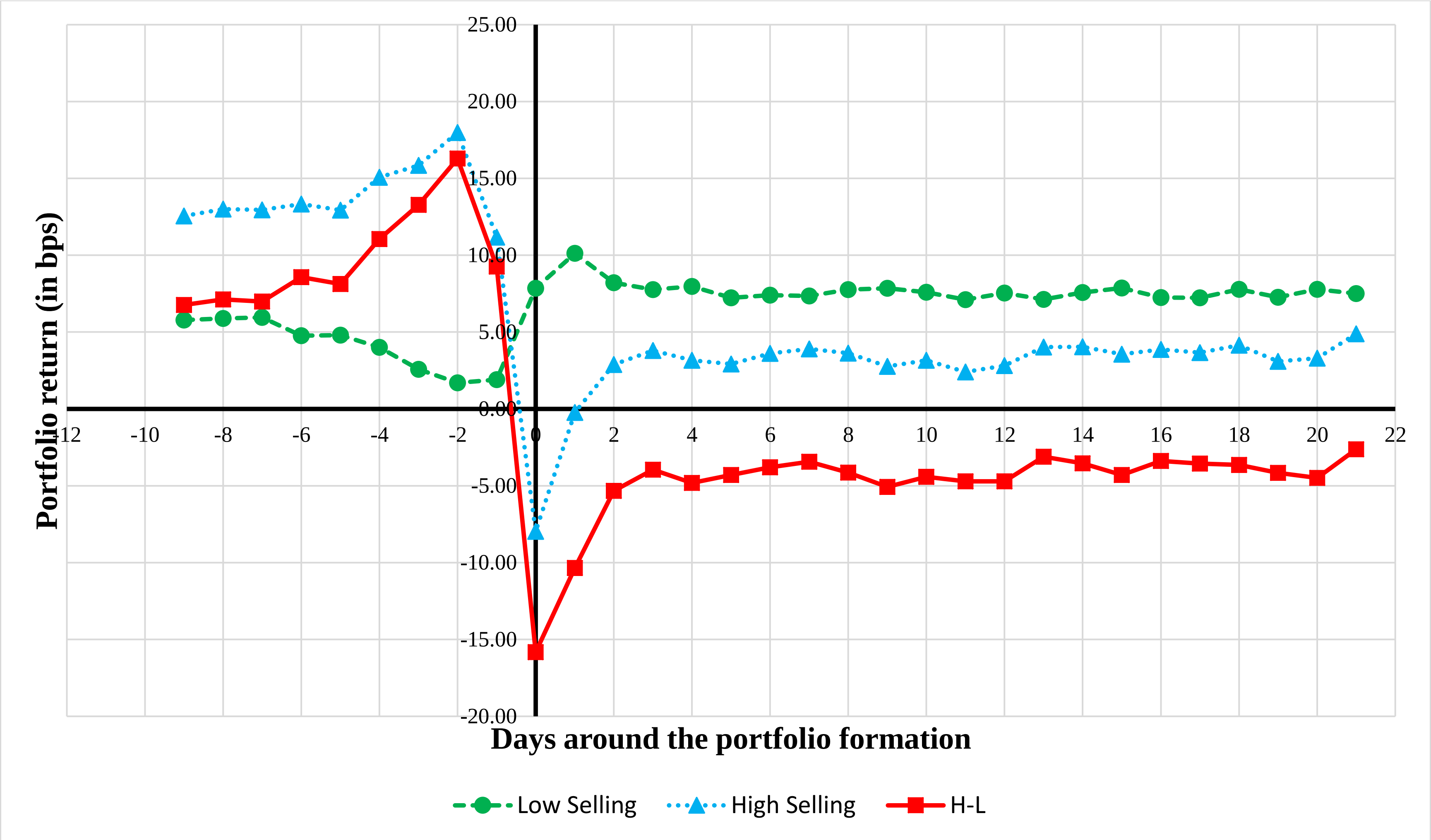

Figure 1. Daily decile Rsel hedge portfolio performance around the formation day

This figure shows the daily portfolio performance for the decile portfolios based on retail selling orders (Rsel) and the long-short Rsel portfolio. On each day, all stocks are ranked and assigned to one of the ten decile portfolios, and then we track the daily returns in the (-10,20) window around the portfolio formation day (i.e. day 0). The long-short portfolio is a zero-cost portfolio that longs the largest Rsel decile stocks and shorts the smallest Rsel decile stocks.

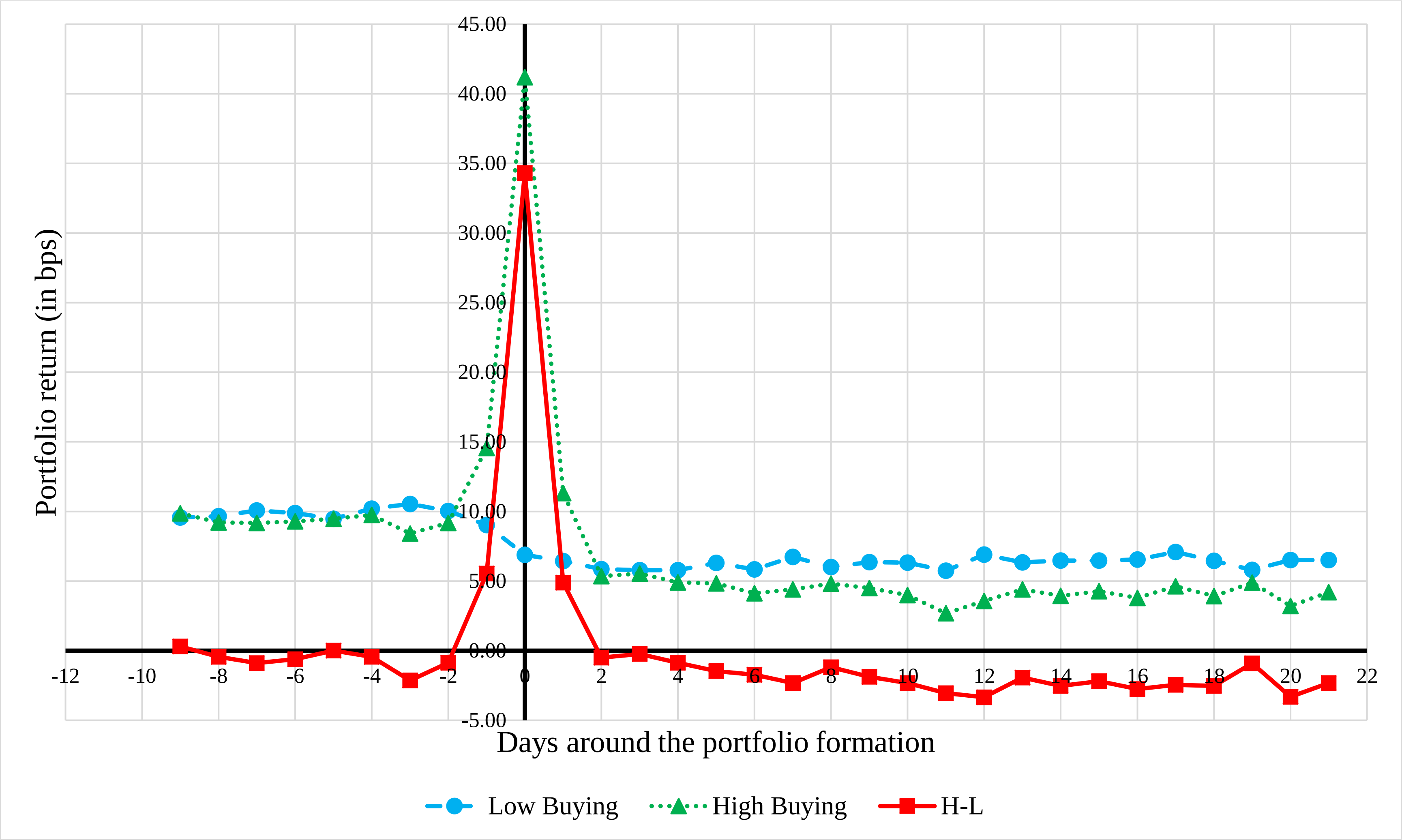

Figure 2. Daily decile Rbuy hedge portfolio performance around the formation day

This figure shows the daily portfolio performance for the decile portfolios based on retail buying orders (Rbuy) and the long-short Rbuy portfolio. On each day, all stocks are ranked and assigned to one of the ten decile portfolios, and then we track the daily returns in the (-10,20) window around the portfolio formation day (i.e. day 0). The long-short portfolio is a zero-cost portfolio that longs the largest Rbuy decile stocks and shorts the smallest Rbuy decile stocks.

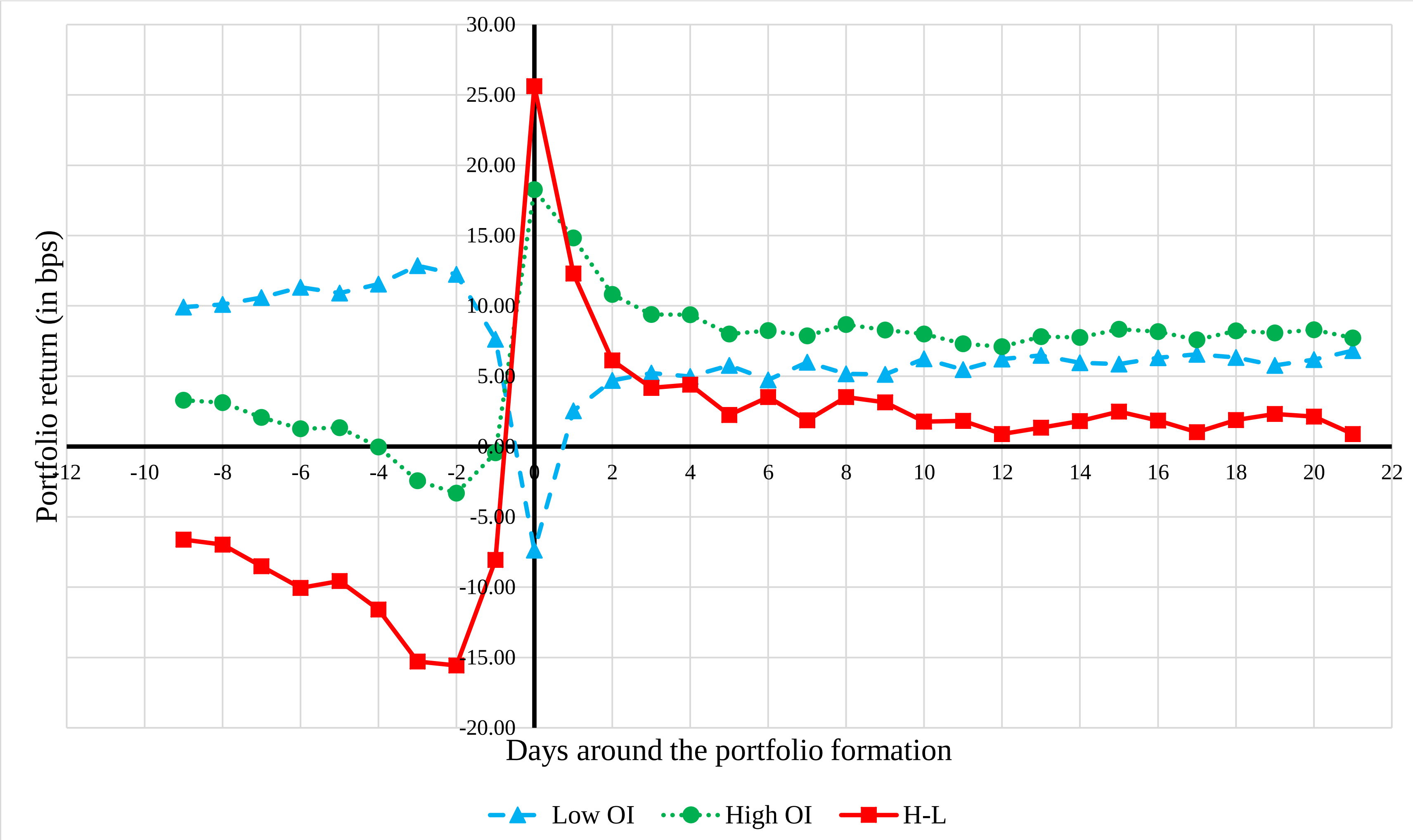

Figure 3. Daily decile OIbjzz hedge portfolio performance around the formation day

This figure shows the daily portfolio performance for the decile portfolios based on retail order imbalance measure (OIbjzz) by Boehmer, Jones, Zhang, and Zhang (2020) and the long-short Rsel portfolio. On each day, all stocks are ranked and assigned to one of the ten decile portfolios, and then we track the daily returns in the (-10,20) window around the portfolio formation day (i.e. day 0). The long-short portfolio is a zero-cost portfolio that longs the largest OIbjzz decile stocks and shorts the smallest OIbjzz decile stocks.

Table 1: Summary statistics

This table reports the summary statistic of our sample data. Panel A reports the pooled distribution of retail investor trading activities. Panel B to Panel D report the time-series average of the mean values of stock characteristics on decile portfolios sorted by aggregate retail selling orders, aggregate retail buying orders, and an order imbalance measure. Panel E reports the time-series average correlation between different variables. In Panel B to E, we rebalance the decile portfolio at the daily frequency. $DVol$ is the average daily trading volume of individual stock, reported in dollars. $SVol$ is the average daily trading volume of individual stock, reported in shares. $NTrd$ is the average of total number of trading orders on each day. $DVolR$, $SVolR$, and $NTrdR$ are defined similar for the retail trading activities. $Rbuy\_DVol$, $Rbuy\_SVol$, $Rbuy\_NTrd$, $Rsel\_DVol$, $Rsel\_SVol$, $Rsel\_NTrd$ are defined similar for retail buying orders and retail selling orders. R_{buy} is the total daily buying volume from retail investors scaled by the total trading volume on that day. R_{sel} is the total daily selling volume from retail investors scaled by the total trading volume on that day. R_{imb} is the difference between $Rbuy$ and $Rsel$. OI_{bjzz} is the retail order imbalance measure proposed by Boehmer, Jones, Zhang, and Zhang (2020), which is the total retail buying orders minus the total retail selling orders scaled by the total retail trading volume, equivalent to the ratio between retail buying orders and retail selling orders. Return t+1 is the equal-weighted average return (in bps) for each portfolio in day t+1. Return t is the equal-weighted average return (in bps) for each portfolio on the formation day (day t). STR21 is the short term reversal factor, defined as the buy and hold return in previous 21 trading days. MAX21 is the maximum daily return during previous 21 trading days. MOM252 is the buy and hold return during previous 252 trading days except the recent 21 trading days. IVOL21 is the idiosyncratic volatility during the previous 21 trading days adjusted by the Fama-French three factor model. Mep is the market capitalization on the portfolio formation day (i.e. day t), in \$Billions. B/M is the most recent available book-to-market equity. OP is the most recent available operating profitability. Spread is the average daily bid-ask spread scaled by the average bid-ask prices during the previous 21 trading days. ILLIQ is the Amihud (2002) illiquidity measure at day t, estimated using the previous 21 trading day data. To t is the stock turnover on day t. To3 is the average daily stock turnover in previous 63 days. IO% is the percentage of shares held by institutional investors in previous quarter. Analysts are the number of analysts covering the stocks in previous month. Dispersion is the standard deviation of the analyst forecasts. All continuous variables are winsorized at 1% and 99% levels. Our sample covers 1762 trading days during 2010 and 2016.

Panel A: Summary statistics of retail trading activities

		N	Mean	STD	Median	Q1	Q3
1	DVol (\$)	4,904,080	38,141,222	94,434,810	4,577,305	695,409	26,921,172
2	SVol	4,904,080	1,069,951	2,448,620	232,859	62,005	864,335
3	NTrd	4,904,080	6,338	11,441	1,968	530	6,563
4	DVolR(\$)	4,904,080	2,310,808	6,757,418	263,288	60,044	1,253,591
5	SvolR	4,904,080	77,067	200,378	14,540	4,442	52,180
6	NTrdR	4,904,080	228	480	65	21	201
7	Rbuy_Dvol (\$)	4,904,080	1,146,970	3,401,315	122,351	25,718	603,972
8	Rbuy_Svol	4,904,080	38,312	101,670	6,788	1,900	25,275
9	Rbuy_NTrd	4,904,080	115	249	31	9	98
10	Rsel_Dvol (\$)	4,904,080	1,158,276	3,386,778	131,576	28,604	627,101
11	Rsel_Svol	4,904,080	38,547	99,759	7,297	2,100	26,381
12	Rsel_NTrd	4,904,080	113	236	32	10	101
13	R_{buy}(%)	4,904,080	4.11	4.69	2.46	1.33	4.89
14	R_{sel}(%)	4,904,080	4.28	4.79	2.62	1.46	5.06
15	R_{imb}(%)	4,904,080	-0.18	4.56	-0.08	-1.21	0.96
16	OI_{bjzz}	4,904,080	-0.03	0.37	-0.02	-0.25	0.19

Average trade size is \$38M/6338=\$6,018; average retail trade size is \$2.3M/228=\$10,135; average retail buying size is \$1.15M/115=\$9,974; average retail selling size is \$1.16M/113=\$10,250. The retail trading size is similar as in Kelley and Tetlock (2013) page 1234, which use data from 2003 to 2007. The results also suggest institutional orders become much smaller after 2010.

(Table 1 continued)

Panel B: Summary statistics of stock characteristics (sorted by aggregated retail selling orders, Rsel)

	1	2	3	4	5	6	7	8	9	10
Rsel (%)	0.57	1.09	1.49	1.90	2.37	2.96	3.78	5.09	7.64	15.90
Rbuy (%)	2.11	2.01	2.19	2.45	2.80	3.28	4.00	5.14	7.14	9.90
OIbjzz	0.32	0.11	0.04	-0.01	-0.04	-0.07	-0.09	-0.11	-0.14	-0.29
Return *t*+1 (‱)	10.03	8.51	7.33	7.19	6.95	7.18	7.24	7.05	4.73	-0.38
Return *t* (‱)	7.97	7.25	7.63	8.09	8.83	8.79	9.84	13.85	23.95	-8.67
STR21 (%)	1.04	1.20	1.29	1.34	1.42	1.41	1.48	1.60	1.95	1.72
Max21 (%)	4.44	4.33	4.38	4.49	4.66	4.90	5.35	6.17	7.45	8.57
MOM252 (%)	15.52	16.84	17.52	17.91	18.21	18.65	18.87	18.79	16.79	11.63
IVOL21 (%)	1.46	1.42	1.45	1.49	1.56	1.66	1.84	2.16	2.65	3.10
Mep ($B)	2.15	3.77	4.91	6.11	7.62	9.46	10.00	6.62	2.42	0.36
B/M	0.66	0.61	0.60	0.60	0.61	0.62	0.65	0.69	0.73	0.85
OP	0.12	0.13	0.14	0.14	0.14	0.13	0.12	0.11	0.07	0.03
Spread	2.92	2.82	2.83	2.88	2.98	3.12	3.38	3.87	4.61	5.20
ILLIQ (10^{-5})	0.09	0.04	0.04	0.04	0.05	0.06	0.08	0.12	0.20	0.55
To *t* (%)	0.60	0.72	0.74	0.75	0.75	0.75	0.76	0.79	0.79	0.52
To3 (%)	0.57	0.72	0.75	0.77	0.77	0.77	0.78	0.81	0.80	0.61
DVol ($M)	15.59	30.09	38.49	46.48	56.09	68.70	76.00	60.31	36.65	4.41
IO%	0.72	0.76	0.76	0.75	0.73	0.70	0.65	0.58	0.45	0.27
Analysts	7.63	9.83	10.54	10.81	10.80	10.53	9.81	8.22	6.06	3.39
Dispersion	0.21	0.19	0.19	0.19	0.20	0.22	0.25	0.30	0.36	0.38

Panel C: Summary statistics of stock characteristics (sorted by aggregated retail buying orders, Rbuy)

	1	2	3	4	5	6	7	8	9	10
Rbuy (%)	0.48	0.97	1.36	1.76	2.22	2.80	3.62	4.93	7.46	15.45
Rsel (%)	2.36	2.20	2.36	2.61	2.95	3.41	4.11	5.26	7.28	10.25
OIbjzz	-0.43	-0.20	-0.11	-0.05	-0.01	0.02	0.05	0.08	0.11	0.25
Return *t*+1 (‱)	6.28	6.31	6.38	6.08	6.18	6.58	6.05	6.37	4.29	11.31
Return *t* (‱)	7.01	5.50	5.27	6.07	6.98	6.76	6.27	2.68	-0.07	41.16
STR21 (%)	1.77	1.54	1.45	1.41	1.39	1.37	1.28	1.21	1.28	1.72
Max21 (%)	4.58	4.36	4.39	4.49	4.66	4.90	5.31	6.08	7.37	8.59
MOM252 (%)	15.89	16.81	17.48	18.00	18.40	18.59	18.95	18.67	16.43	11.50
IVOL21 (%)	1.48	1.42	1.44	1.49	1.56	1.66	1.83	2.14	2.64	3.11
Mep (B)	2.07	3.67	4.79	5.97	7.42	9.02	9.70	7.34	2.93	0.50
B/M	0.68	0.62	0.61	0.60	0.61	0.62	0.64	0.69	0.73	0.84
OP	0.12	0.13	0.14	0.14	0.14	0.13	0.13	0.11	0.07	0.03
Spread	2.89	2.81	2.83	2.89	2.99	3.13	3.39	3.86	4.60	5.22
ILLIQ (10^{-5})	0.08	0.04	0.04	0.04	0.05	0.06	0.08	0.11	0.20	0.56
To *t* (%)	0.58	0.69	0.72	0.74	0.74	0.75	0.76	0.79	0.82	0.58
To3 (%)	0.57	0.70	0.74	0.75	0.76	0.77	0.78	0.81	0.82	0.63
DVol ($M)	14.79	28.19	36.71	44.61	54.58	66.00	72.97	65.44	42.00	7.53
IO%	0.71	0.76	0.76	0.75	0.73	0.70	0.66	0.58	0.46	0.28
Analysts	7.43	9.61	10.39	10.73	10.75	10.50	9.85	8.49	6.41	3.63
Dispersion	0.21	0.19	0.19	0.19	0.20	0.22	0.25	0.30	0.36	0.38

(Table 1 continued)

Panel D: Summary statistics of stock characteristics (sorted by aggregated retail orders imbalance, OIbjzz)

	-10	-9	-8	-7	-6	-5	-4	-3	-2	-1	1	2	3	4	5	6	7	8	9	10
OIbjzz	-0.79	-0.58	-0.44	-0.34	-0.27	-0.21	-0.15	-0.10	-0.06	-0.02	0.02	0.06	0.09	0.14	0.18	0.24	0.31	0.40	0.53	0.76
Rbuy (%)	1.07	1.91	2.31	2.59	2.83	3.07	3.28	3.50	3.74	3.92	4.18	4.33	4.47	4.63	4.79	5.04	5.40	5.96	6.93	9.73
Rsel (%)	9.37	6.82	5.81	5.22	4.86	4.61	4.42	4.29	4.21	4.06	4.03	3.89	3.72	3.53	3.32	3.12	2.89	2.61	2.21	1.32
Return *t*+1	1.34	3.51	3.46	2.77	3.42	3.76	4.48	5.53	5.02	5.16	5.68	5.38	6.37	7.76	8.73	9.98	11.47	11.18	14.64	15.91
Return *t*	-9.51	-4.70	-3.15	-0.47	2.49	3.08	6.32	6.22	9.72	12.15	16.34	19.35	17.91	16.17	13.77	14.34	12.82	14.40	16.63	20.17
STR21 (%)	1.69	1.69	1.68	1.69	1.64	1.66	1.68	1.70	1.67	1.67	1.73	1.64	1.54	1.41	1.29	1.15	0.99	0.84	0.70	0.47
Max21 (%)	5.67	5.43	5.37	5.34	5.34	5.38	5.42	5.46	5.51	5.55	5.63	5.64	5.60	5.56	5.50	5.44	5.39	5.37	5.39	5.55
MOM252	13.71	14.97	15.88	16.54	17.16	17.71	18.06	18.69	19.30	19.21	20.02	19.70	19.45	18.40	17.85	17.07	16.14	15.37	14.00	12.03
IVOL21 (%)	1.96	1.85	1.83	1.82	1.82	1.83	1.84	1.86	1.88	1.89	1.92	1.92	1.92	1.91	1.89	1.88	1.87	1.87	1.89	1.99
Mep	0.84	1.67	2.41	3.27	4.41	5.56	6.92	8.16	9.31	9.58	10.36	9.79	8.66	7.17	5.79	4.44	3.30	2.41	1.62	0.78
B/M	0.81	0.73	0.69	0.67	0.65	0.63	0.62	0.62	0.61	0.63	0.61	0.61	0.62	0.62	0.64	0.64	0.66	0.68	0.73	0.82
OP	0.09	0.10	0.11	0.11	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.11	0.11	0.11	0.11	0.10	0.09
Spread	3.56	3.45	3.41	3.39	3.38	3.38	3.38	3.39	3.42	3.43	3.46	3.48	3.48	3.48	3.48	3.48	3.48	3.50	3.55	3.69
ILLIQ (10^{-5})	0.34	0.18	0.13	0.11	0.08	0.08	0.07	0.06	0.06	0.10	0.05	0.06	0.06	0.07	0.08	0.09	0.12	0.14	0.21	0.43
To *t* (%)	0.33	0.45	0.54	0.61	0.69	0.74	0.81	0.86	0.92	0.92	1.01	0.99	0.96	0.90	0.83	0.76	0.67	0.59	0.47	0.32
To3 (%)	0.39	0.51	0.60	0.67	0.74	0.78	0.83	0.88	0.92	0.90	0.97	0.96	0.92	0.88	0.82	0.76	0.68	0.61	0.50	0.35
DVol ($M)	5.09	11.47	17.06	23.33	32.30	41.02	51.51	62.78	75.08	84.96	96.36	87.48	74.08	59.42	46.69	35.59	25.93	18.55	11.49	4.48
IO%	0.52	0.60	0.63	0.65	0.66	0.67	0.67	0.67	0.68	0.66	0.68	0.67	0.67	0.67	0.66	0.66	0.64	0.63	0.59	0.50
Analysts	4.80	6.29	7.36	8.14	8.99	9.60	10.25	10.71	11.15	11.04	11.50	11.26	10.87	10.31	9.66	9.01	8.17	7.33	6.23	4.68
Dispersion	0.29	0.26	0.24	0.23	0.23	0.23	0.22	0.23	0.22	0.23	0.23	0.23	0.23	0.23	0.23	0.24	0.24	0.24	0.26	0.28

Panel E: Correlation matrix between different retail trading activities and some typical stock characteristics

No:	Variable	OI_{bjzz}	R_{imb}	R_{buy}	R_{sel}	R_{vol}	Return *t*	STR21	Max21	MOM252	IVOL21	Ln(Mep)	Ln(B/M)
(1)	OI_{bjzz}	1.00	0.94	0.45	-0.38	0.03	0.03	-0.03	0.01	-0.01	0.02	0.00	-0.01
(2)	R_{imb}	0.75	1.00	0.39	-0.38	0.00	0.04	-0.03	0.00	0.00	0.01	0.02	-0.01
(3)	R_{buy}	0.39	0.47	1.00	0.57	0.86	0.00	-0.03	0.28	-0.09	0.37	-0.37	0.02
(4)	R_{sel}	-0.35	-0.51	0.51	1.00	0.87	-0.03	-0.01	0.29	-0.09	0.36	-0.39	0.04
(5)	R_{vol}	0.02	-0.03	0.86	0.86	1.00	-0.02	-0.03	0.32	-0.11	0.41	-0.47	0.06
(6)	Return *t*	0.03	0.05	0.03	-0.02	0.01	1.00	0.19	0.02	0.01	-0.02	0.03	0.00
(7)	STR21	-0.03	-0.01	0.00	0.01	0.00	0.21	1.00	0.25	0.02	-0.01	0.07	0.01
(8)	Max21	0.00	-0.01	0.28	0.28	0.31	0.10	0.38	1.00	-0.15	0.81	-0.44	0.01
(9)	MOM252	0.00	0.00	-0.06	-0.06	-0.07	0.00	0.00	-0.10	1.00	-0.18	0.21	-0.03
(10)	IVOL21	0.01	-0.01	0.37	0.37	0.42	0.04	0.11	0.84	-0.11	1.00	-0.56	0.00
(11)	Ln(Mep)	0.00	0.02	-0.45	-0.46	-0.53	0.00	0.03	-0.38	0.14	-0.50	1.00	-0.24
(12)	Ln(B/M)	-0.01	-0.01	0.06	0.07	0.08	0.01	0.01	0.01	-0.02	0.00	-0.21	1.00

Table 2. Daily portfolio analysis based on aggregate retail orders

This table reports the time-series average returns or alphas (in bps) of daily rebalanced decile portfolios sorted by their aggregate retail orders. Panel A and Panel B report the results based on aggregate retail selling orders (Rsel) and aggregate retail buying orders (Rbuy) respectively. Excess return is the average returns in excess of the risk-free rate. Alpha is the intercept from the regression of daily excess returns on risk factors specified by an asset pricing model. The factor models include: the CAPM, the Fama-French three-factor model, and a four-factor model that includes Fama-French three factors and Carhart momentum factor. Long-Short return or Alpha is the return or alpha of a zero-cost portfolio that longs the corresponding high retail measure decile portfolio and shorts the low retail measure decile portfolio (i.e., H – L). We also report the long-short hedge portfolio return based on the 2nd and 9th decile portfolio. The t-statistics shown in parentheses are computed based on standard errors with Newey-West corrections. ** and * indicate statistical significance at the 1% and 5% levels, respectively, using two-tailed tests. The sample period is from January 2010 to December 2016, covering total 1762 trading days.

Panel A: decile portfolio based on aggregate retail selling orders (Rsel)

	Equal-weighted returns				Value-weighted returns			
	Excess Return	CAPM Alpha	3-factor Alpha	4-factor Alpha	Excess Return	CAPM Alpha	3-factor Alpha	4-factor Alpha
1 (Low)	10.03	4.11	4.66	4.72	8.60	2.88	3.15	3.19
	(3.92)	(4.42)	(11.18)	(11.74)	(3.63)	(4.03)	(5.81)	(5.91)
2	8.51	2.44	2.88	2.97	7.04	1.31	1.46	1.48
	(3.28)	(2.89)	(7.13)	(7.80)	(3.00)	(2.36)	(3.10)	(3.13)
3	7.33	1.23	1.65	1.75	6.41	0.75	0.86	0.87
	(2.85)	(1.58)	(4.11)	(4.59)	(2.80)	(1.58)	(1.91)	(1.94)
4	7.19	1.04	1.46	1.55	6.51	0.92	1.00	1.01
	(2.76)	(1.32)	(3.93)	(4.27)	(2.90)	(2.10)	(2.36)	(2.40)
5	6.95	0.77	1.19	1.29	5.41	-0.02	0.00	0.03
	(2.68)	(0.97)	(3.26)	(3.68)	(2.52)	(-0.05)	(0.00)	(0.08)
6	7.18	0.97	1.41	1.51	5.87	0.67	0.64	0.65
	(2.65)	(1.12)	(3.56)	(3.93)	(2.83)	(1.69)	(1.63)	(1.65)
7	7.24	0.89	1.38	1.47	3.94	-1.27	-1.32	-1.31
	(2.58)	(0.92)	(2.87)	(3.22)	(1.87)	(-2.98)	(-3.18)	(-3.16)
8	7.05	0.57	1.14	1.31	4.35	-1.17	-1.17	-1.20
	(2.35)	(0.45)	(1.68)	(2.06)	(1.98)	(-1.92)	(-1.93)	(-1.97)
9	4.73	-1.74	-1.10	-0.86	3.88	-2.34	-2.27	-2.32
	(1.40)	(-1.05)	(-0.99)	(-0.81)	(1.41)	(-1.87)	(-1.92)	(-1.95)
10 (High)	-0.38	-5.41	-4.92	-4.77	-0.55	-6.27	-5.89	-5.85
	(-0.13)	(-3.02)	(-3.43)	(-3.38)	(-0.18)	(-3.86)	(-4.23)	(-4.22)
H – L	-10.42**	-9.52**	-9.58**	-9.50**	-9.14**	-9.14**	-9.04**	-9.04**
(*t*-stat)	(-7.10)	(-6.01)	(-6.11)	(-6.06)	(-5.77)	(-5.71)	(-5.94)	(-5.94)
(9)-(2)	-3.78**	-4.18**	-3.98**	-3.83**	-3.16*	-3.66**	-3.74**	-3.80**
(*t*-stat)	(-2.83)	(-3.22)	(-3.33)	(-3.23)	(-2.31)	(-2.67)	(-2.83)	(-2.86)

(Table 2, continued)

Panel B: decile portfolio based on aggregate retail buying orders (Rbuy)

	Equal-weighted returns				Value-weighted returns			
	Excess Return	CAPM Alpha	3-factor Alpha	4-factor Alpha	Excess Return	CAPM Alpha	3-factor Alpha	4-factor Alpha
1 (Low)	6.28	0.51	1.05	1.11	5.78	0.29	0.56	0.59
	(2.50)	(0.54)	(2.68)	(2.87)	(2.52)	(0.42)	(1.14)	(1.22)
2	6.31	0.25	0.71	0.80	6.30	0.65	0.82	0.84
	(2.46)	(0.31)	(2.14)	(2.43)	(2.77)	(1.33)	(1.99)	(2.04)
3	6.38	0.26	0.69	0.78	6.05	0.43	0.53	0.55
	(2.49)	(0.34)	(1.95)	(2.34)	(2.72)	(0.89)	(1.21)	(1.26)
4	6.08	-0.08	0.34	0.43	6.01	0.44	0.51	0.52
	(2.33)	(-0.10)	(0.91)	(1.18)	(2.66)	(0.98)	(1.20)	(1.21)
5	6.18	-0.04	0.39	0.49	4.93	-0.54	-0.52	-0.50
	(2.32)	(-0.04)	(1.04)	(1.34)	(2.25)	(-1.34)	(-1.30)	(-1.24)
6	6.58	0.32	0.76	0.85	5.56	0.25	0.23	0.24
	(2.45)	(0.38)	(1.86)	(2.26)	(2.62)	(0.64)	(0.58)	(0.60)
7	6.05	-0.25	0.24	0.35	5.30	0.08	0.05	0.05
	(2.16)	(-0.26)	(0.49)	(0.79)	(2.56)	(0.23)	(0.13)	(0.14)
8	6.37	-0.12	0.44	0.60	4.51	-0.91	-0.91	-0.92
	(2.14)	(-0.10)	(0.65)	(0.94)	(2.04)	(-1.55)	(-1.57)	(-1.57)
9	4.29	-2.19	-1.55	-1.31	6.73	0.77	0.80	0.80
	(1.31)	(-1.39)	(-1.52)	(-1.37)	(2.62)	(0.69)	(0.75)	(0.75)
10 (High)	11.31	6.21	6.69	6.85	7.42	1.39	1.66	1.61
	(3.52)	(3.28)	(4.28)	(4.46)	(2.30)	(0.74)	(0.93)	(0.91)
H – L	5.03**	5.70**	5.65**	5.75**	1.64	1.11	1.10	1.01
(*t*-stat)	(3.21)	(3.39)	(3.39)	(3.47)	(0.84)	(0.56)	(0.57)	(0.53)
(9)-(2)	-2.03	-2.44*	-2.26*	-2.11*	0.43	0.12	-0.02	-0.03
(*t*-stat)	(-1.63)	(-2.03)	(-2.05)	(-1.97)	(0.35)	(0.09)	(-0.01)	(-0.03)

Table 3. 10×10 double sorted portfolios based on aggregate retail selling and retail buying orders

This table reports the 10×10 double sorted portfolio analysis results based on the retail buying measure and retail selling measure. In Panel A, we first sort stocks into decile groups based on the aggregate retail buying orders. To construct the 10×10 portfolios, we further sort the stocks within each decile group into decile groups based on the aggregate retail selling orders. In Panel B, we first sort stocks by retail selling orders and then sort stock by retail buying orders. The time series average returns or Fama-French four-factor alphas (in bps) of the decile portfolios are reported. The t-statistics shown in parentheses are computed based on standard errors with Newey-West corrections. ** and * indicate statistical significance at the 1% and 5% levels, respectively, using two-tailed tests. To save space, we only report the results for the 1st, 2nd, 5th, 6th, 9th, and 10th decile portfolios.

Panel A: 10×10 double sorted portfolios first by aggregate retail buying orders (Rbuy)

	Equal-weighted returns						Value-weighted returns					
	Low Buy	2	5	6	9	High Buy	Low Buy	2	5	6	(9)	High Buy
1 (Low sell)	10.79	9.06	9.81	11.10	12.83	18.34	8.18	9.11	7.40	10.16	8.65	11.67
2	8.60	8.28	7.69	9.31	13.01	20.40	8.13	7.96	6.86	6.88	5.77	12.57
5	8.16	6.70	4.94	7.73	5.95	12.82	7.08	5.24	5.15	5.49	8.30	7.56
6	3.95	5.52	6.23	7.12	4.16	7.38	3.39	6.70	4.92	7.22	7.17	-0.38
9	5.13	4.92	5.23	3.27	-1.97	1.16	4.59	5.44	2.86	5.14	-1.99	-0.27
10 (High sell)	1.48	3.67	2.76	-0.20	-9.15	1.69	2.13	4.51	2.65	3.34	-8.96	-3.13
H – L	-9.30**	-5.39**	-7.05**	-11.30**	-21.97**	-16.65**	-6.05**	-4.60**	-4.75*	-6.81**	-17.61**	-14.79**
(*t*-stat)	(-5.69)	(-3.56)	(-4.02)	(-5.97)	(-8.81)	(-5.30)	(-3.19)	(-2.80)	(-2.46)	(-3.05)	(-6.55)	(-4.94)
FF4 Alpha	-8.95**	-4.98**	-6.64**	-10.78**	-21.05**	-15.93**	-6.15**	-4.41**	-4.71*	-6.52**	-17.25**	-13.23**
(*t*-stat)	(-5.47)	(-3.36)	(-3.76)	(-5.75)	(-8.04)	(-4.97)	(-3.20)	(-2.68)	(-2.41)	(-2.94)	(-6.38)	(-4.23)

Panel B: 10×10 double sorted portfolios first by aggregate retail selling orders (Rsel)

	Equal-weighted returns						Value-weighted returns					
	Low Sell	2	5	6	9	High Sell	Low Sell	2	5	6	(9)	High Sell
1 (Low buy)	9.10	6.30	5.63	6.38	2.40	-1.74	7.13	4.79	4.92	7.72	5.12	3.30
2	9.52	6.68	4.89	4.39	2.60	-2.75	7.20	6.41	5.07	4.31	3.65	0.37
5	8.43	7.80	6.93	6.24	0.65	-5.63	7.42	6.90	4.62	6.34	4.92	-3.47
6	9.95	7.14	5.36	4.92	2.33	-6.70	11.54	7.53	5.62	6.23	3.41	-4.89
9	11.88	10.44	8.19	11.02	10.46	8.93	10.45	8.07	7.80	7.62	9.67	5.71
10 (High buy)	15.29	13.71	13.05	16.64	23.26	17.94	9.86	11.12	6.94	10.31	11.59	10.59
H – L	6.19**	7.41**	7.42**	10.26**	20.86**	19.68**	2.72	6.33**	2.03	2.59	6.47*	7.29*
(*t*-stat)	(3.75)	(4.45)	(4.46)	(5.42)	(6.86)	(6.99)	(1.47)	(3.56)	(0.95)	(1.22)	(2.08)	(2.38)
FF4 Alpha	6.33**	7.60**	7.50**	10.60**	21.82**	20.62**	2.12	6.10**	2.12	2.63	6.85*	8.42**
(*t*-stat)	(3.80)	(4.56)	(4.50)	(5.56)	(6.97)	(7.10)	(1.14)	(3.45)	(1.00)	(1.25)	(2.22)	(2.60)

Table 4. Fama-MacBeth cross-sectional return regressions

This table reports the results from Fama-MacBeth cross-sectional regressions. All stock characteristics are standardized (N~(0,1)) to make the results comparable. Panel A and B show the results based on equal-weighted least square (EWLS) and value-weight least square (VWLS) regressions. The dependent variable is a firm's daily stock return (in bps). The explanatory variable of interest is the aggregate retail selling orders (Rsel), aggregate retail buying orders (Rbuy), and aggregate retail order imbalance (OIbjzz). The control variables include: the Lee and Ready (1991) total trading order imbalance (TOI_LR), the stock returns in previous 3 days (Return(t), Return(t-1), and Return(t-2)), the daily turnover in previous day (To(t)), the logarithm of market capitalization in previous day (Ln(SIZE)), market beta (Beta252), the logarithm of book-to-market equity (Ln(B/M)), annual operating profitability (OP), total asset growth (TAG), momentum (MOM252), Short-term reversal (STR21), idiosyncratic volatility (IVOL21), maximum daily return (MAX21), and average daily turnover ratio during previous 3 months (TO3). The table reports the time-series daily averages of the estimated coefficients. The t-statistics are shown in parentheses using the Newey and West (1987) corrected standard errors with up to twelve lags. ** and * indicate statistical significance at the 1% and 5% levels, respectively, using two-tailed tests. The sample period is from January 2010 to December 2016, covering total 1762 trading days.

Panel A: EW results

	(1)	(2)	(3)	(4)	(5)	(6)
Rsel	-3.39**			-4.82**	-2.28**	
	(-10.45)			(-16.36)	(-6.22)	
Rbuy		2.27**		3.98**		0.78*
		(7.16)		(13.87)		(2.07)
OIbjzz			3.19**		2.43**	2.91**
			(22.04)		(13.55)	(14.81)
TOI_LR	1.63**	1.85**	1.53**	0.94**	1.32**	1.46**
	(8.07)	(9.08)	(7.59)	(4.65)	(6.54)	(7.18)
Return(t)	-6.30**	-6.35**	-6.29**	-6.35**	-6.31**	-6.33**
	(-11.59)	(-11.70)	(-11.58)	(-11.71)	(-11.61)	(-11.67)
Return(t-1)	-1.81**	-1.84**	-1.80**	-1.80**	-1.81**	-1.82**
	(-5.09)	(-5.18)	(-5.06)	(-5.11)	(-5.12)	(-5.15)
Return(t-2)	-1.86**	-1.87**	-1.83**	-1.82**	-1.83**	-1.83**
	(-5.45)	(-5.50)	(-5.38)	(-5.35)	(-5.38)	(-5.38)
To(t)	0.61	1.03*	0.78	0.68	0.60	0.82
	(1.33)	(2.25)	(1.70)	(1.49)	(1.32)	(1.79)
Ln(SIZE)	-2.30**	-0.46	-1.16*	-1.47**	-1.92**	-0.95
	(-4.46)	(-0.90)	(-2.28)	(-2.82)	(-3.72)	(-1.84)
Beta252	-1.24	-0.37	-0.67	-0.82	-1.04	-0.56
	(-1.45)	(-0.43)	(-0.79)	(-0.96)	(-1.21)	(-0.66)
Ln(B/M)	0.37	0.54	0.50	0.46	0.43	0.52
	(0.79)	(1.18)	(1.09)	(1.00)	(0.94)	(1.12)
OP	0.65	1.10**	0.95*	0.87*	0.75	1.00**
	(1.69)	(2.87)	(2.45)	(2.26)	(1.95)	(2.61)
TAG	-0.62	-0.70*	-0.69*	-0.65*	-0.64	-0.68*
	(-1.86)	(-2.12)	(-2.09)	(-1.97)	(-1.95)	(-2.05)
MOM252	0.75	0.72	0.73	0.76	0.75	0.76
	(1.40)	(1.34)	(1.37)	(1.43)	(1.41)	(1.42)
STR21	-1.93**	-1.95**	-1.86**	-1.82**	-1.83**	-1.83**
	(-3.63)	(-3.68)	(-3.51)	(-3.44)	(-3.47)	(-3.45)
IVOL21	-1.68**	-2.94**	-2.44**	-2.27**	-1.99**	-2.64**
	(-2.64)	(-4.57)	(-3.72)	(-3.61)	(-3.14)	(-4.14)
MAX21	1.28*	1.49*	1.43*	1.34*	1.33*	1.42*
	(2.18)	(2.51)	(2.42)	(2.28)	(2.26)	(2.40)
TO3	-1.97**	-2.47**	-2.23**	-2.12**	-2.03**	-2.28**
	(-3.93)	(-4.84)	(-4.36)	(-4.23)	(-4.04)	(-4.50)

(Table 4, continued)

Panel B: VW results

	(1)	(2)	(3)	(4)	(5)	(6)
Rsel	-2.60**			-3.79**	-1.97**	
	(-4.59)			(-7.42)	(-3.23)	
Rbuy		-0.15		1.88**		-1.50*
		(-0.29)		(3.81)		(-2.47)
OIbjzz			1.56**		1.22**	2.03**
			(7.62)		(5.31)	(7.94)
TOI_LR	0.63*	0.80**	0.56*	0.49	0.46	0.51
	(2.29)	(2.95)	(2.02)	(1.76)	(1.66)	(1.84)
Return(t)	-2.17**	-2.23**	-2.15**	-2.18**	-2.15**	-2.16**
	(-3.93)	(-4.04)	(-3.91)	(-3.94)	(-3.90)	(-3.91)
Return(t-1)	-1.09*	-1.05*	-1.04*	-1.09*	-1.09*	-1.07*
	(-2.31)	(-2.23)	(-2.22)	(-2.32)	(-2.32)	(-2.28)
Return(t-2)	-0.59	-0.57	-0.60	-0.56	-0.57	-0.55
	(-1.25)	(-1.22)	(-1.27)	(-1.19)	(-1.20)	(-1.17)
To(t)	-0.05	-0.02	-0.06	-0.09	-0.09	-0.11
	(-0.11)	(-0.05)	(-0.14)	(-0.19)	(-0.20)	(-0.24)
Ln(SIZE)	-0.45	-0.73	-0.83	-0.55	-0.56	-0.60
	(-0.98)	(-1.59)	(-1.77)	(-1.21)	(-1.22)	(-1.30)
Beta252	-0.21	-0.13	-0.10	-0.17	-0.18	-0.17
	(-0.20)	(-0.12)	(-0.09)	(-0.16)	(-0.17)	(-0.16)
Ln(B/M)	-0.11	-0.04	-0.02	-0.08	-0.08	-0.06
	(-0.33)	(-0.12)	(-0.06)	(-0.24)	(-0.23)	(-0.19)
OP	0.34	0.42	0.45	0.37	0.38	0.39
	(0.81)	(1.03)	(1.11)	(0.90)	(0.91)	(0.94)
TAG	-0.01	-0.10	-0.15	-0.05	-0.05	-0.06
	(-0.04)	(-0.32)	(-0.48)	(-0.15)	(-0.17)	(-0.21)
MOM252	0.68	0.64	0.65	0.68	0.68	0.67
	(0.99)	(0.93)	(0.93)	(0.97)	(0.97)	(0.96)
STR21	-2.09**	-2.12**	-1.96**	-2.06**	-2.03**	-2.03**
	(-3.31)	(-3.35)	(-3.10)	(-3.25)	(-3.21)	(-3.20)
IVOL21	-2.76**	-3.18**	-3.18**	-2.89**	-2.89**	-2.97**
	(-3.67)	(-4.20)	(-4.14)	(-3.82)	(-3.84)	(-3.93)
MAX21	2.73**	2.81**	2.77**	2.75**	2.76**	2.77**
	(4.11)	(4.21)	(4.12)	(4.14)	(4.15)	(4.16)
TO3	-0.31	-0.42	-0.42	-0.34	-0.33	-0.33
	(-0.64)	(-0.86)	(-0.85)	(-0.70)	(-0.68)	(-0.66)

Table 5. Weekly rebalanced portfolio analysis based on aggregate retail orders

This table reports the average returns or alphas (in bps) of weekly rebalanced portfolios sorted by their aggregate retail orders in previous week. Panel A and B report the results based on aggregate selling orders (Rsel) and aggregate buying orders (Rbuy). Excess return is the average returns in excess of the risk-free rate. Alpha is the intercept from the regression of weekly excess returns on risk factors. The factor models include: the CAPM, the Fama-French three-factor model, and a four-factor model that includes Fama-French three factors and Carhart momentum factor. Long-Short return or Alpha is the return or alpha of a zero-cost portfolio that longs the high retail measure decile portfolio and shorts the low retail measure decile portfolio (i.e., H – L). The t-statistics shown in parentheses are computed based on standard errors with Newey-West corrections. ** and * indicate statistical significance at the 1% and 5% levels, respectively, using two-tailed tests. The sample period is from January 2010 to December 2016, covering total 365 trading weeks. To save space, we only report the results for the 1st, 2nd, 5th, 6th, 9th, and 10th decile portfolios.

Panel A: weekly decile portfolio based on aggregate retail selling orders (Rsel)

	Equal-weighted returns				Value-weighted returns			
	Excess Return	CAPM Alpha	3-factor Alpha	4-factor Alpha	Excess Return	CAPM Alpha	3-factor Alpha	4-factor Alpha
1 (Low)	39.25	10.95	13.87	14.34	36.06	8.67	10.05	10.18
	(3.43)	(2.83)	(6.23)	(6.19)	(3.53)	(3.02)	(3.96)	(3.97)
2	31.55	2.72	5.15	5.55	30.97	4.08	4.90	4.86
	(2.78)	(0.82)	(2.54)	(2.70)	(3.00)	(1.54)	(2.04)	(2.00)
5	32.42	2.99	5.55	5.98	26.89	1.47	1.57	1.61
	(2.96)	(0.94)	(3.43)	(3.67)	(3.08)	(0.95)	(1.01)	(1.03)
6	32.38	2.45	5.32	5.73	26.26	1.82	1.54	1.54
	(2.77)	(0.73)	(3.10)	(3.36)	(3.07)	(1.08)	(0.96)	(0.97)
9	17.05	-13.52	-9.33	-7.94	32.23	0.13	0.74	0.12
	(1.22)	(-2.10)	(-1.98)	(-1.66)	(2.30)	(0.01)	(0.08)	(0.01)
10 (High)	6.18	-19.08	-15.86	-15.07	-8.79	-37.82	-34.97	-34.41
	(0.43)	(-2.16)	(-2.10)	(-2.03)	(-0.56)	(-3.82)	(-3.82)	(-3.81)
H – L	-33.07**	-30.03**	-29.73**	-29.41**	-44.85**	-46.50**	-45.02**	-44.59**
(*t*-stat)	(-4.19)	(-3.73)	(-3.79)	(-3.73)	(-4.81)	(-4.88)	(-4.87)	(-4.83)

Panel B: weekly decile portfolio based on aggregate retail buying orders (Rbuy)

	Equal-weighted returns				Value-weighted returns			
	Excess Return	CAPM Alpha	3-factor Alpha	4-factor Alpha	Excess Return	CAPM Alpha	3-factor Alpha	4-factor Alpha
1 (Low)	27.21	0.41	3.51	3.89	29.01	2.85	4.39	4.55
	(2.58)	(0.11)	(1.95)	(2.07)	(2.92)	(0.95)	(1.80)	(1.85)
2	27.81	-1.31	1.24	1.58	29.35	2.54	3.30	3.18
	(2.50)	(-0.41)	(0.86)	(1.07)	(2.99)	(1.17)	(1.68)	(1.57)
5	31.77	2.16	4.72	5.19	27.02	1.18	1.23	1.31
	(2.82)	(0.65)	(2.68)	(2.90)	(2.97)	(0.61)	(0.63)	(0.67)
6	29.27	-0.34	2.36	2.71	23.75	-1.30	-1.59	-1.61
	(2.50)	(-0.09)	(1.22)	(1.45)	(2.88)	(-0.79)	(-0.99)	(-0.99)
9	26.04	-4.91	-0.79	0.72	26.93	-2.95	-2.53	-2.46
	(1.78)	(-0.67)	(-0.15)	(0.15)	(2.26)	(-0.40)	(-0.36)	(-0.35)
10 (High)	19.10	-7.10	-3.83	-2.84	7.28	-23.71	-21.28	-20.94
	(1.35)	(-0.87)	(-0.55)	(-0.41)	(0.50)	(-2.26)	(-2.11)	(-2.08)
H – L	-8.11	-7.51	-7.34	-6.73	-21.72*	-26.55*	-25.67*	-25.49*
(*t*-stat)	(-1.01)	(-0.94)	(-0.93)	(-0.85)	(-1.99)	(-2.42)	(-2.43)	(-2.39)

Table 6. Buy and hold returns in the following 21 trading day

This table reports the average buy and hold returns or alphas (in percentage) of daily rebalanced portfolios sorted by their aggregate retail orders. Panel A and B report the results based on aggregate selling orders (Rsel) and aggregate buying orders (Rbuy). On each day, we establish the decile portfolios, and hold them for 21 trading days. Excess return is the average buy and hold return in excess of the 21-day cumulative risk-free rate. Alpha is the intercept from the regression of excess returns on risk factors. We compound the daily risk factors for 21 trading days. The factor models include: the CAPM, the Fama-French three-factor model, and a four-factor model that includes Fama-French three factors and Carhart momentum factor. Long-Short return or Alpha is the return or alpha of a zero-cost portfolio that longs the corresponding high retail measure decile portfolio and shorts the low retail measure decile portfolio (i.e., H – L). The t-statistics shown in parentheses are computed based on standard errors with Newey-West corrections. ** and * indicate statistical significance at the 1% and 5% levels, respectively, using two-tailed tests. To save space, we only report the results for the 1st, 2nd, 5th, 6th, 9th, and 10th decile portfolios.

Panel A: decile portfolio based on aggregate retail selling orders (Rsel)

	Equal-weighted returns				Value-weighted returns			
	Excess Return	CAPM Alpha	3-factor Alpha	4-factor Alpha	Excess Return	CAPM Alpha	3-factor Alpha	4-factor Alpha
1 (Low)	1.55	0.26	0.45	0.47	1.44	0.22	0.32	0.33
	(4.26)	(1.94)	(10.74)	(11.12)	(4.39)	(2.62)	(5.64)	(5.71)
2	1.45	0.13	0.29	0.31	1.38	0.17	0.24	0.24
	(4.00)	(1.15)	(6.95)	(7.60)	(4.32)	(2.38)	(4.13)	(4.15)
5	1.29	-0.05	0.09	0.12	1.15	0.01	0.02	0.02
	(3.54)	(-0.48)	(2.40)	(3.62)	(3.89)	(0.34)	(0.50)	(0.69)
6	1.28	-0.08	0.07	0.10	1.12	0.04	0.02	0.02
	(3.45)	(-0.73)	(1.90)	(3.04)	(3.98)	(1.07)	(0.66)	(0.61)
9	0.79	-0.74	-0.52	-0.44	1.27	-0.01	0.02	0.03
	(1.75)	(-3.53)	(-3.95)	(-3.44)	(3.52)	(-0.04)	(0.12)	(0.17)
10 (High)	0.43	-0.92	-0.73	-0.65	0.66	-0.66	-0.56	-0.53
	(1.01)	(-3.76)	(-3.84)	(-3.48)	(1.76)	(-3.98)	(-4.08)	(-3.91)
H – L	-1.11**	-1.18**	-1.18**	-1.12**	-0.77**	-0.88**	-0.88**	-0.86**
(*t*-stat)	(-5.31)	(-5.73)	(-5.86)	(-5.54)	(-4.91)	(-5.28)	(-5.57)	(-5.40)

Panel B: decile portfolio based on aggregate retail buying orders (Rbuy)

	Equal-weighted returns				Value-weighted returns			
	Excess Return	CAPM Alpha	3-factor Alpha	4-factor Alpha	Excess Return	CAPM Alpha	3-factor Alpha	4-factor Alpha
1 (Low)	1.25	-0.00	0.19	0.20	1.25	0.08	0.18	0.19
	(3.54)	(-0.02)	(4.79)	(4.89)	(3.93)	(0.90)	(3.44)	(3.50)
2	1.29	-0.02	0.14	0.17	1.28	0.09	0.15	0.16
	(3.59)	(-0.16)	(3.71)	(4.70)	(4.10)	(1.45)	(3.06)	(3.21)
5	1.30	-0.05	0.09	0.12	1.17	0.02	0.03	0.04
	(3.54)	(-0.45)	(2.49)	(3.28)	(3.92)	(0.56)	(0.76)	(0.87)
6	1.30	-0.06	0.09	0.12	1.13	0.03	0.02	0.02
	(3.49)	(-0.54)	(2.43)	(3.63)	(3.94)	(0.85)	(0.55)	(0.59)
9	0.88	-0.65	-0.44	-0.35	1.22	-0.01	-0.00	0.03
	(1.94)	(-3.17)	(-3.28)	(-2.74)	(3.59)	(-0.07)	(-0.00)	(0.25)
10 (High)	0.71	-0.66	-0.47	-0.38	0.77	-0.56	-0.50	-0.47
	(1.63)	(-2.63)	(-2.39)	(-1.99)	(1.96)	(-2.83)	(-2.89)	(-2.73)
H – L	-0.54*	-0.66**	-0.66**	-0.58**	-0.48*	-0.64**	-0.68**	-0.66**
(*t*-stat)	(-2.47)	(-3.06)	(-3.18)	(-2.82)	(-2.48)	(-3.17)	(-3.76)	(-3.61)

Table 7. Portfolio order imbalance in each 10×10 double sorted portfolios

This table reports the portfolio's time-series average retail order imbalance (in %) in the 10×10 double sorted portfolios based on the retail buying measure and retail selling measure. Both the *ex ante* (as of day t) and *ex post* (as of day t+1) retail order imbalance measures are reported. Retail order imbalance (Rimb) is defined as the net retail buying orders scaled by the total trading volume on that day, i.e. (Rbuy-Rsel). In Panel A, we first sort stocks into decile groups based on the aggregate retail buying orders. To construct the 10×10 portfolios, we further sort the stocks within each decile group into finer decile groups based on the aggregate retail selling orders. In Panel B, we reverse the sorting order. The percentage numbers below the portfolio index number are the average retail buying order or the average retail selling orders in that decile portfolio. The t-statistics shown in parentheses are computed based on standard errors with Newey-West corrections. ** and * indicate statistical significance at the 1% and 5% levels, respectively, using two-tailed tests. To save space, we only report the results for the 1st, 2nd, 5th, 6th, 9th, and 10th decile portfolios.

Panel A: Portfolio order imbalance in the 10×10 double sorted portfolios first by aggregate retail buying orders (Rbuy)

	Rimb as of formation day t						Rimb as of day t+1					
	Low Buy	2	5	6	9	High Buy	Low Buy	2	5	6	9	High Buy
	0.47%	0.97%	2.22%	2.80%	7.46%	15.72%	2.32%	2.16%	2.88%	3.35%	7.06%	10.22%
1 (Low sell)	0.14	0.52	1.50	1.99	6.19	13.62	-0.18	-0.10	0.00	0.03	0.13	0.21
2	-0.07	0.19	0.96	1.34	4.64	11.61	-0.20	-0.09	-0.01	0.04	0.25	0.13
5	-0.66	-0.41	0.09	0.27	1.57	6.04	-0.27	-0.17	-0.09	-0.04	0.08	-0.09
6	-0.94	-0.64	-0.20	-0.05	0.77	4.64	-0.35	-0.21	-0.14	-0.08	0.06	-0.23
9	-3.28	-2.27	-1.97	-2.07	-3.96	-0.73	-0.63	-0.47	-0.41	-0.44	-0.62	-0.87
10 (High sell)	-9.48	-6.95	-6.86	-7.44	-11.81	-8.47	-1.17	-0.84	-0.86	-0.82	-1.10	-1.18
H – L	-9.62**	-7.47**	-8.36**	-9.43**	-18.00**	-22.09**	-0.99**	-0.75**	-0.86**	-0.85**	-1.23**	-1.40**
(*t*-stat)	(-48.72)	(-109.61)	(-117.36)	(-116.20)	(-83.74)	(-65.92)	(-17.53)	(-17.92)	(-19.09)	(-16.54)	(-14.65)	(-11.88)

Panel B: Portfolio order imbalance in the 10×10 double sorted portfolios first by aggregate retail selling orders (Rsel)

	Rimb as of formation day t						Rimb as of day t+1					
	Low Sell	2	5	6	9	High Sell	Low Sell	2	5	6	9	High Sell
	0.55%	1.09%	2.37%	2.96%	7.65%	16.19%	2.59%	2.36%	3.08%	3.54%	7.31%	10.78%
1 (Low buy)	-0.25	-0.70	-1.75	-2.27	-6.60	-14.24	-0.26	-0.31	-0.45	-0.50	-0.89	-1.33
2	-0.08	-0.39	-1.24	-1.64	-5.21	-12.57	-0.16	-0.22	-0.32	-0.37	-0.74	-1.19
5	0.43	0.18	-0.32	-0.50	-1.78	-7.17	-0.08	-0.09	-0.15	-0.17	-0.30	-0.81
6	0.67	0.39	-0.03	-0.15	-0.79	-5.43	-0.06	-0.06	-0.09	-0.10	-0.22	-0.72
9	2.70	1.83	1.65	1.80	3.68	0.21	0.05	0.05	0.07	0.16	0.10	-0.69
10 (High buy)	8.63	6.14	6.11	6.76	10.93	7.59	0.14	0.19	0.17	0.20	-0.27	-0.82
H – L	8.87**	6.83**	7.86**	9.03**	17.54**	21.83**	0.40**	0.50**	0.62**	0.70**	0.61**	0.51**
(*t*-stat)	(46.83)	(99.38)	(102.07)	(104.67)	(81.14)	(64.83)	(6.90)	(12.30)	(13.33)	(14.08)	(8.17)	(3.88)

Table 8. Portfolio performance and retail trading activities around intense individual trading activities

This table presents the portfolio performance around intense individual trading measures. Panel A and B show the results based on retail selling order and retail buying orders. On each trading day, we rank stocks into decile groups according to the two retail trading measures. We then report average daily portfolio return and the retail trading actitivities during the (-20, 20) window around the formation day (i.e. Day 0). The reported returns and other variables are the time series equal-weighted average within each portfolio. Dvol is the total dollar amount trading volume. Rsel is the percentage of retail orders. Rbuy is the percentage of retail buying orders. Rimb is the difference between Rbuy and Rsel. The t-statistics shown in parentheses are computed based on standard errors with Newey-West corrections. ** and * indicate statistical significance at the 1% and 5% levels, respectively, using two-tailed tests.

		Day (-20,-16)	Day (-15,-11)	Day (-10,-6)	Day (-5,-3)	Day (-2)	Day (-1)	Day (0)	Day (1)	Day (2)	Day (3,5)	Day (6,10)	Day (11,15)	Day (15,20)
Panel A: Decile portfolio based on aggregate retail selling orders (Rsel)														
Decile 1 Low sell	Dvol($M)	15.07**	15.13**	15.15**	15.14**	15.13**	15.17**	16.25**	15.59**	15.68**	15.53**	15.44**	15.35**	15.33**
	Rsel(%)	2.47**	2.45**	2.42**	2.36**	2.30**	2.22**	0.57**	2.23**	2.31**	2.37**	2.42**	2.45**	2.48**
	Rbuy (%)	2.30**	2.29**	2.26**	2.23**	2.19**	2.15**	2.11**	2.19**	2.23**	2.27**	2.30**	2.32**	2.34**
	Rimb (%)	-0.17**	-0.16**	-0.15**	-0.13**	-0.11**	-0.07**	1.49**	-0.04**	-0.08**	-0.10**	-0.12**	-0.13**	-0.14**
	Return (‱)	6.80**	6.21**	5.71*	3.78	1.48	1.84	7.78**	10.01**	8.35**	7.74**	7.62**	7.40**	7.44**
Decile 10 High Sell	Dvol($M)	4.86**	4.83**	4.80**	4.85**	4.87**	4.84**	4.53**	4.41**	4.44**	4.48**	4.51**	4.55**	4.59**
	Rsel(%)	9.82**	9.89**	9.99**	10.13**	10.28**	10.45**	15.88**	10.50**	10.33**	10.19**	10.05**	9.95**	9.87**
	Rbuy (%)	9.41**	9.46**	9.55**	9.66**	9.75**	9.88**	9.89**	9.80**	9.69**	9.59**	9.49**	9.42**	9.35**
	Rimb (%)	-0.40**	-0.42**	-0.44**	-0.47**	-0.52**	-0.56**	-5.73**	-0.69**	-0.64**	-0.59**	-0.55**	-0.52**	-0.52**
	Return (‱)	9.54**	10.86**	12.40**	14.43**	17.76**	10.83**	-11.73**	-0.41	2.99	3.34	3.39	3.32	3.61
H-L	Rimb (%)	-0.24**	-0.26**	-0.28**	-0.34**	-0.41**	-0.49**	-7.22**	-0.65**	-0.56**	-0.49**	-0.43**	-0.39**	-0.38**
	(*t*-stat)	(-9.01)	(-9.70)	(-10.85)	(-12.14)	(-13.99)	(-17.48)	(-85.50)	(-22.58)	(-19.22)	(-18.10)	(-16.34)	(-14.73)	(-14.31)
	Return(‱)	2.75	4.65**	6.69**	10.64**	16.27**	8.99**	-19.51**	-10.42**	-5.36**	-4.40**	-4.23**	-4.09**	-3.83**
	(*t*-stat)	(1.92)	(3.24)	(4.79)	(7.14)	(9.74)	(5.25)	(-10.82)	(-7.10)	(-3.73)	(-3.42)	(-3.18)	(-3.14)	(-2.99)
Panel A: Decile portfolio based on aggregate retail buying orders (Rbuy)														
Decile 1 Low Buy	Dvol($M)	14.71**	14.81**	14.85**	14.82**	14.80**	14.72**	15.49**	14.79**	14.78**	14.70**	14.62**	14.55**	14.52**
	Rsel(%)	2.58**	2.56**	2.54**	2.50**	2.46**	2.42**	2.36**	2.39**	2.44**	2.47**	2.50**	2.53**	2.54**
	Rbuy (%)	2.31**	2.28**	2.23**	2.17**	2.10**	2.02**	0.48**	2.04**	2.11**	2.17**	2.24**	2.27**	2.30**
	Rimb (%)	-0.27**	-0.28**	-0.30**	-0.33**	-0.36**	-0.40**	-1.82**	-0.35**	-0.32**	-0.30**	-0.27**	-0.25**	-0.24**
	Return (‱)	9.09**	9.42**	9.73**	10.13**	10.17**	9.06**	6.74**	6.26*	5.79*	6.01*	6.29**	6.36**	6.51**
Decile 10 High Buy	Dvol($M)	7.87**	7.84**	7.80**	7.85**	7.95**	7.89**	7.68**	7.53**	7.51**	7.48**	7.49**	7.57**	7.58**
	Rsel(%)	9.68**	9.74**	9.81**	9.91**	10.00**	10.10**	10.23**	10.27**	10.15**	10.05**	9.94**	9.86**	9.79**
	Rbuy (%)	9.46**	9.53**	9.64**	9.79**	9.95**	10.14**	15.42**	10.15**	9.96**	9.80**	9.66**	9.54**	9.46**
	Rimb (%)	-0.21**	-0.20**	-0.17**	-0.12**	-0.06*	0.03	4.93**	-0.12**	-0.19**	-0.24**	-0.29**	-0.31**	-0.33**
	Return (‱)	7.87**	8.58**	9.42**	9.19**	8.96**	14.16**	36.33**	11.29**	5.40	5.04	4.45	3.84	4.07
H-L	Rimb (%)	0.06*	0.08**	0.13**	0.22**	0.30**	0.43**	6.75**	0.23**	0.13**	0.05	-0.02	-0.06*	-0.09**
	(*t*-stat)	(2.16)	(3.12)	(4.97)	(7.90)	(10.36)	(14.25)	(73.73)	(7.56)	(4.35)	(1.95)	(-0.71)	(-2.21)	(-3.31)
	Return(‱)	-1.22	-0.85	-0.31	-0.94	-1.22	5.10*	29.59**	5.03**	-0.39	-0.97	-1.84	-2.52	-2.44
	(*t*-stat)	(-0.84)	(-0.59)	(-0.21)	(-0.61)	(-0.65)	(2.52)	(13.20)	(3.21)	(-0.26)	(-0.71)	(-1.37)	(-1.88)	(-1.86)

Table 9. Additional analysis on fear or greed sentiment

This table reports the results from Fama-MacBeth cross-sectional regressions. All stock characteristics are standardized (N~(0,1)) to make the results comparable. Panel A and B show the results based on equal-weighted least square (EWLS) and value-weight least square (VWLS) regressions. The dependent variable is the stock's daily return (in bps). Besides the control variables in Table 4, we include additional interaction terms, including interactions with small size dummy (Size<Q20%), high idiosyncratic volatility dummy (IVol>Q80%), high VIX dummy (VIX_high), and low market return dummy (MKT_low). The t-statistics shown in parentheses are computed based on standard errors with Newey-West corrections. ** and * indicate statistical significance at the 1% and 5% levels, respectively, using two-tailed tests. The sample period is from January 2010 to December 2016, covering total 1762 trading days.

Panel A: EWLS Fama-MacBeth regression results

	(1)	(2)	(3)	(4)
Rsel	-2.84**	-2.54**	-1.39**	-0.81**
	(-6.64)	(-8.00)	(-7.10)	(-4.22)
Rsel×Size<Q20%	-1.13*			
	(-2.18)			
Rsel×IVol>Q80%		-2.20**		
		(-4.55)		
Rsel×VIX_high			-2.00**	
			(-6.68)	
Rsel×MKT_low				-2.58**
				(-10.63)
Control variables as in Table 4	yes	yes	yes	yes

Panel B: VWLS Fama-MacBeth regression results

	(1)	(2)	(3)	(4)
Rsel	-2.52**	-2.38**	-1.00**	-0.55
	(-4.13)	(-4.04)	(-2.93)	(-1.49)
Rsel×Size<Q20%	-2.40**			
	(-3.54)			
Rsel×IVol>Q80%		-2.44*		
		(-2.12)		
Rsel×VIX_high			-1.60**	
			(-3.66)	
Rsel×MKT_low				-2.05**
				(-4.94)
Control variables as in Table 4	yes	yes	yes	yes

Table 10. Investor mood: Weekday effects

This table reports the weekday performance of the weekly rebalanced portfolios sorted by their aggregate retail selling orders (Rsel). Panel A and B report the results based on equal weighted portfolio and value weighted portfolio. At the end of each week, we estimate the aggregate retail selling orders for each stock during the week, and establish the decile portfolios. We then report the portfolio performance in each weekday in the following week. To save space, we only report the results for the 1st, 2nd, 5th, 6th, 9th, and 10th decile portfolios. Long-Short excess return (H-L Exret) or 4-factor Alpha is the return or alpha of a zero-cost portfolio that longs the corresponding high retail measure decile portfolio and shorts the low retail measure decile portfolio (i.e., H – L). The t-statistics shown in parentheses are computed based on standard errors with Newey-West corrections. ** and * indicate statistical significance at the 1% and 5% levels, respectively, using two-tailed tests.

Panel A: EW portfolio results based on aggregate retail selling orders (Rsel)

	Low Rsel	2	5	6	9	High Rsel	H – L Exret	4-factor Alpha
Mon	0.73	-2.09	-2.16	-2.08	-2.58	-8.15	-8.88*	-9.07*
	(0.12)	(-0.33)	(-0.33)	(-0.31)	(-0.35)	(-1.08)	(-2.04)	(-2.05)
Tue	14.11	11.52	11.54	12.89	5.99	-0.66	-14.77**	-11.71**
	(2.36)	(1.84)	(1.79)	(1.92)	(0.91)	(-0.13)	(-4.26)	(-3.76)
Wed	7.76	6.19	7.46	6.86	3.58	4.69	-3.07	-0.42
	(1.62)	(1.30)	(1.55)	(1.39)	(0.71)	(1.23)	(-0.95)	(-0.15)
Thu	10.70	10.61	9.87	9.73	5.19	2.01	-8.70*	-6.29*
	(1.85)	(1.82)	(1.69)	(1.67)	(0.88)	(0.41)	(-2.36)	(-2.15)
Fri	7.40	6.28	6.95	6.26	8.35	14.31	6.91	6.64*
	(1.25)	(1.02)	(1.16)	(0.98)	(1.30)	(3.09)	(1.90)	(2.27)

Panel B: VW portfolio results based on aggregate retail selling orders (Rsel)

	Low Rsel	2	5	6	9	High Rsel	H – L Exret	4-factor Alpha
Mon	-3.14	-3.53	-2.52	-1.68	1.34	-9.13	-5.99	-5.98
	(-0.53)	(-0.60)	(-0.51)	(-0.35)	(0.17)	(-1.06)	(-1.07)	(-1.08)
Tue	12.55	10.58	9.87	10.83	16.69	0.09	-12.46**	-12.25**
	(2.23)	(1.80)	(1.81)	(2.05)	(2.06)	(0.01)	(-2.66)	(-2.74)
Wed	8.33	7.95	6.94	6.93	6.95	-1.76	-10.09**	-6.85*
	(1.87)	(1.75)	(1.62)	(1.59)	(1.13)	(-0.39)	(-3.11)	(-2.10)
Thu	11.59	10.97	9.58	7.16	9.50	-4.36	-15.96**	-14.76**
	(2.23)	(1.95)	(1.88)	(1.50)	(1.16)	(-0.67)	(-3.99)	(-4.34)
Fri	7.49	5.76	3.90	3.49	-1.00	7.29	-0.20	-2.73
	(1.34)	(1.00)	(0.72)	(0.67)	(-0.15)	(1.16)	(-0.05)	(-0.74)

Table 11. Retail trading activities around S&P 500 index addition and deletion

This table shows the time-series average of daily stock returns and retail trading activities around the S&P 500 index addition or deletion. Panel A and B present the results using addition and deletion respectively. EDay is defined as the effective addition/deletion day, which is Day 0. We focus on a window of 5 weeks (25 trading days) before and 4 week (20 trading days) after the effective day. Daily stock returns and the retail trading activates around the EDay are reported. Dvol is the average daily dollar trading volume. Rbuy is the daily aggregate retail buying orders. Rsel is the aggregate retail selling orders. Rimb is the difference between Rbuy and Rsel. Both the raw returns and market-adjusted returns are reported. The t-statistics shown in parentheses are computed based on bootstrap method with 10,000 iterations.

Panel A: Retail trading activities around the S&P500 index addition day

	(-25,-21)	(-20,-16)	(-15,-11)	(-10,-6)	(-5,-3)	-2	-1	EDay	1	2	(3,5)	(6,10)	(11,15)	(16,20)
Dvol($B)	0.15**	0.17**	0.18**	0.21**	0.30**	2.16**	0.32**	0.22**	0.22**	0.23**	0.21**	0.20**	0.16**	0.16**
Rsel(%)	2.73**	2.67**	2.54**	2.69**	2.46**	2.17**	2.03**	2.16**	2.35**	2.24**	2.39**	2.46**	2.41**	2.46**
Rbuy(%)	2.70**	2.78**	2.69**	2.71**	2.54**	2.24**	1.65**	2.24**	2.46**	2.37**	2.48**	2.43**	2.46**	2.48**
Rimb(%)	-0.01	0.11	0.16*	0.01	0.08	0.08	-0.30	0.08	0.11	0.13	0.09	-0.03	0.05	0.02
(*t*-stat)	(-0.10)	(1.21)	(2.45)	(0.12)	(0.92)	(0.81)	(-1.03)	(0.86)	(0.68)	(1.10)	(1.14)	(-0.46)	(0.90)	(0.32)
Return(‱)	14.61	16.69	14.15	17.03*	15.52	-7.51	-33.14*	3.69	-3.48	9.58	-29.21*	15.86	1.55	21.38**
(*t*-stat)	(1.69)	(1.52)	(1.37)	(1.99)	(0.96)	(-0.38)	(-1.97)	(0.13)	(-0.17)	(0.49)	(-2.38)	(1.70)	(0.19)	(2.85)
ExRet(‱)	6.66	21.06	8.37	12.37	12.07	-13.23	-53.95**	-1.19	1.46	-2.54	-23.63*	-0.05	-6.42	9.00
(*t*-stat)	(0.89)	(1.94)	(0.93)	(1.64)	(0.85)	(-0.80)	(-3.08)	(-0.05)	(0.09)	(-0.16)	(-2.35)	(-0.01)	(-0.90)	(1.37)

Panel B: Retail trading activities around the S&P500 index deletion day

	(-25,-21)	(-20,-16)	(-15,-11)	(-10,-6)	(-5,-3)	-2	-1	EDay	1	2	(3,5)	(6,10)	(11,15)	(16,20)
Dvol($B)	0.07**	0.07**	0.07**	0.08**	0.08**	0.12**	0.55**	0.11**	0.09**	0.09**	0.07**	0.07**	0.07**	0.08**
Rsel(%)	3.16**	3.02**	3.14**	3.22**	2.87**	2.73**	2.90**	2.29**	2.96**	3.17**	3.03**	3.24**	2.86**	2.98**
Rbuy(%)	3.06**	3.01**	3.34**	3.42**	2.90**	2.61**	2.78**	2.08**	3.02**	3.22**	3.08**	3.23**	3.19**	3.08**
Rimb(%)	-0.09	-0.01	0.20	0.15	0.03	-0.13	-0.12	-0.21	0.06	0.05	0.02	-0.01	0.32**	0.10
(*t*-stat)	(-0.75)	(-0.11)	(1.79)	(0.78)	(0.26)	(-0.49)	(-0.57)	(-1.57)	(0.38)	(0.21)	(0.12)	(-0.10)	(3.49)	(0.77)
Return(‱)	-11.99	-21.41	45.83*	2.18	-20.78	55.74	17.48	55.75	-9.73	82.80*	2.56	15.82	-16.51	37.68*
(*t*-stat)	(-0.74)	(-1.20)	(2.47)	(0.14)	(-1.16)	(1.42)	(0.59)	(1.66)	(-0.23)	(1.97)	(0.12)	(0.99)	(-0.98)	(2.30)
ExRet(‱)	-16.19	-14.95	25.42	-5.75	-21.12	41.20	18.19	44.09	-10.43	59.84	-6.01	5.49	-20.66	30.79
(*t*-stat)	(-1.05)	(-1.08)	(1.53)	(-0.43)	(-1.28)	(1.14)	(0.63)	(1.40)	(-0.26)	(1.68)	(-0.31)	(0.36)	(-1.36)	(1.84)

Table 12. Portfolio return and individual trading around the Earnings Announcement day

This table presents the portfolio returns and individual trading activities around the earnings announcement days. In each quarter, we estimate the stocks' standard earning announcement surprise (SUEs) based on the actual EPS and the analyst census EPS in previous month, and then rank stocks into 1 of the 5 quintiles according to their SUE measure. Panel A to C report the results for the highest SUE group, middle SUE group, and lowest SUE group. We report the time-series average of the portfolio return and the associated retail trading measures. Both raw returns and the market adjusted returns are reported. The t-statistics shown in parentheses are computed based on standard errors with Newey-West corrections.

	Day (-20,-16)	Day (-15,-11)	Day (-10,-6)	Day (-5,-3)	Day (-2)	Day (-1)	EADay (0)	Day (1)	Day (-2)	Day (3,5)	Day (6,10)	Day (11,15)	Day (15,20)
Panel A: Earnings announcement with extreme positive earnings surprise, ranked in Q5 (Top 20%)													
Dvol($M)	23.60**	23.45**	23.69**	23.94**	25.20**	31.93**	63.62**	37.59**	30.62**	27.91**	25.62**	24.80**	24.66**
Rsel(%)	5.44**	5.43**	5.43**	5.40**	5.30**	5.39**	5.54**	5.81**	5.69**	5.61**	5.55**	5.54**	5.57**
Rbuy(%)	5.22**	5.26**	5.27**	5.30**	5.47**	5.91**	5.43**	5.40**	5.26**	5.26**	5.31**	5.31**	5.28**
Rimb(%)	-0.22**	-0.17**	-0.16**	-0.10*	0.16**	0.52**	-0.11*	-0.41**	-0.43**	-0.35**	-0.24**	-0.23**	-0.29**
(*t*-stat)	(-7.45)	(-5.32)	(-10.29)	(-2.37)	(3.42)	(8.86)	(-2.32)	(-10.37)	(-10.04)	(-8.81)	(-10.20)	(-7.43)	(-11.12)
Return(‱	16.03**	13.69**	11.48*	7.35	7.93	35.22**	321.93**	19.35*	10.05	10.57	3.27	9.96*	9.53**
(*t*-stat)	(3.08)	(3.27)	(2.48)	(1.35)	(1.46)	(6.00)	(25.36)	(2.16)	(1.41)	(1.64)	(0.39)	(2.08)	(3.39)
ExRet(‱)	6.01	3.84	2.31	1.52	6.61*	34.56**	320.21**	15.21*	2.98	10.03*	3.69	5.77	4.75
(*t*-stat)	(1.94)	(1.12)	(0.54)	(0.30)	(2.09)	(6.07)	(25.17)	(2.71)	(0.74)	(2.67)	(1.06)	(1.86)	(1.94)
Panel B: Earnings announcement with moderate earnings surprise, ranked in Q3 (middle 20%)													
Dvol($M)	83.11**	84.03**	84.40**	88.19**	92.08**	116.70**	231.23**	131.00**	107.59**	95.75**	88.11**	87.44**	84.83**
Rsel(%)	2.60**	2.56**	2.55**	2.50**	2.49**	2.60**	2.85**	2.77**	2.69**	2.62**	2.61**	2.59**	2.58**
Rbuy(%)	2.50**	2.48**	2.47**	2.45**	2.53**	2.86**	2.75**	2.62**	2.51**	2.48**	2.48**	2.47**	2.47**
Rimb(%)	-0.11**	-0.09**	-0.08*	-0.06	0.04	0.26**	-0.10**	-0.15**	-0.18**	-0.14**	-0.13**	-0.12**	-0.11**
(*t*-stat)	(-5.46)	(-3.24)	(-2.75)	(-1.85)	(1.45)	(8.59)	(-5.74)	(-6.68)	(-5.36)	(-5.52)	(-5.07)	(-4.28)	(-5.29)
Return(‱	6.52	8.39**	8.80**	10.14**	3.89	11.22**	38.60**	7.99**	3.91	0.56	4.38	5.77	7.15**
(*t*-stat)	(1.44)	(2.79)	(5.45)	(3.55)	(1.39)	(3.25)	(5.36)	(2.90)	(1.06)	(0.14)	(0.88)	(1.24)	(3.56)
ExRet(‱)	0.39	-0.10	0.23	2.48	1.29	8.77**	32.47**	2.05	-3.54*	0.86	3.52**	2.34	2.94*
(*t*-stat)	(0.28)	(-0.09)	(0.18)	(1.14)	(0.54)	(5.35)	(5.92)	(1.26)	(-2.40)	(0.77)	(3.50)	(1.75)	(2.48)
Panel C: Earnings announcement with extreme negative earnings surprise, ranked in Q1 (Bottom 20%)													
Dvol($M)	17.35**	17.21**	17.65**	17.79**	18.61**	22.27**	46.24**	26.17**	21.90**	19.42**	18.40**	17.73**	17.06**
Rsel(%)	5.69**	5.67**	5.70**	5.63**	5.63**	5.67**	5.63**	6.00**	5.76**	5.65**	5.72**	5.69**	5.69**
Rbuy(%)	5.43**	5.52**	5.51**	5.53**	5.67**	5.94**	5.47**	5.57**	5.47**	5.43**	5.45**	5.47**	5.42**
Rimb(%)	-0.26**	-0.15**	-0.19**	-0.10**	0.04	0.27**	-0.17**	-0.42**	-0.29**	-0.22**	-0.26**	-0.21**	-0.27**
(*t*-stat)	(-10.88)	(-4.50)	(-5.77)	(-3.11)	(1.16)	(3.83)	(-3.85)	(-6.30)	(-5.79)	(-14.33)	(-7.84)	(-12.86)	(-8.62)
Return(‱	9.10	5.90	0.29	-4.53	-13.28	-23.27**	-352.90**	-43.06**	-21.01**	-1.35	2.75	9.74*	4.37
(*t*-stat)	(1.74)	(1.29)	(0.06)	(-1.09)	(-2.03)	(-2.86)	(-33.69)	(-3.28)	(-3.73)	(-0.19)	(0.35)	(2.73)	(1.39)
ExRet(‱)	-1.07	-4.34	-8.43	-9.21*	-12.88**	-23.65**	-353.52**	-47.22**	-27.03**	-1.41	2.79	4.97*	-1.03
(*t*-stat)	(-0.32)	(-1.18)	(-1.96)	(-2.48)	(-4.56)	(-5.39)	(-41.34)	(-5.22)	(-10.66)	(-0.33)	(0.76)	(2.09)	(-0.34)

Table 13. Retail trading and Earnings Announcements: Fama-MacBeth regression

This table presents the coefficients estimated from quarterly Fama-MacBeth regressions of cumulative returns (CAR) on different retail trading activities over different period. RET[0] is the stock return on the earnings announcement day. CAR[X,Y] refers to the cumulative return over the period t+X to t+Y. Rsel, Rbuy, and OIbjzz are the corresponding retail trading measures on the previous day of the earnings announcement day. Rsel5, Rbuy5, and OIbjzz5 are the corresponding average retail trading measures on the previous 5 days before the earnings announcement day. Rsel10, Rbuy10, and OIbjzz10 are the corresponding average retail trading measures on the previous 10 days before the earnings announcement day. We regress CAR on different retail trading measures separately, but report them together to save space. All the control variables in Table 4 are also included in the regression, but the coefficients are not reported. The t-statistics shown in parentheses are computed based on standard errors with Newey-West corrections. ** and * indicate statistical significance at the 1% and 5% levels, respectively, using two-tailed tests.

Panel A: Retail trading activities on day (-1)

	RET[0]	CAR[-1,1]	CAR[0,2]	CAR[2,5]	CAR[2,10]
Rsel	-0.30**	-0.38**	-0.43**	-0.13**	-0.24**
	(-10.87)	(-11.43)	(-14.93)	(-8.70)	(-4.92)
Rbuy	-0.18**	-0.27**	-0.32**	-0.10**	-0.14**
	(-7.10)	(-15.56)	(-13.37)	(-6.99)	(-3.92)
OIbjzz	0.15**	0.15**	0.16**	0.01	0.07*
	(6.77)	(5.59)	(6.84)	(0.76)	(2.40)
Control	Yes	Yes	Yes	Yes	Yes

Panel B: Average retail trading activities during day (-1) to day (-5)

	RET[0]	CAR[-1,1]	CAR[0,2]	CAR[2,5]	CAR[2,10]
Rsel5	-0.34**	-0.47**	-0.56**	-0.19**	-0.33**
	(-11.67)	(-14.47)	(-17.86)	(-6.41)	(-5.01)
Rbuy5	-0.29**	-0.41**	-0.48**	-0.15**	-0.26**
	(-10.29)	(-9.32)	(-14.24)	(-4.77)	(-4.13)
OIbjzz5	0.07**	0.08*	0.11**	0.04**	0.08**
	(3.07)	(2.51)	(3.79)	(2.72)	(4.77)
Control	Yes	Yes	Yes	Yes	Yes

Panel C: Average retail trading activities during day (-1) to day (-10)

	RET[0]	CAR[-1,1]	CAR[0,2]	CAR[2,5]	CAR[2,10]
Rsel10	-0.38**	-0.52**	-0.62**	-0.19**	-0.33**
	(-14.13)	(-19.37)	(-25.43)	(-6.08)	(-4.39)
Rbuy10	-0.32**	-0.45**	-0.53**	-0.17**	-0.29**
	(-15.02)	(-13.39)	(-23.61)	(-5.18)	(-3.86)
OIbjzz10	0.09**	0.10**	0.13**	0.04**	0.08**
	(4.65)	(3.79)	(4.70)	(4.22)	(6.39)
Control	Yes	Yes	Yes	Yes	Yes

Online Appendix for

Fear or Greed? How Retail Trades Move Markets?

This online appendix provide additional test results for the paper.

In Table OA1, we report the decile portfolio analysis results based on the retail order imbalance measure proposed by Boehmer, Jones, Zhang, and Zhang (2020), i.e., OIbjzz as defined in equation (1). This measure is equivalent to the ratio of retail buying orders and retail selling orders. Our results confirm that the retail order imbalance measure could positively predict the cross-sectional stock returns during our sample period.

In Table OA2, we exclude the micro-cap stocks whose market capitalization is smaller than the 20% breakpoint of all the NYSE stocks. We find the aggregate retail selling order still predict future stock returns. While the retail buying order, even using equal-weighted portfolio, loses return predictability, and the sign of the long-short portfolio even flips. Besides, the long-short hedge returns based on retail selling orders are almost twice as that based on retail order imbalance.

In Table OA3, we divide the whole sample into 6 sub-samples, with each year as a sub-sample. We then repeat the portfolio analysis within each year, and report the results year by year.

In Table OA4, we present alternative construction of retail trading measures to show the robustness. Specifically, instead of using the raw retail trading level as the measure, we compare the current retail trading measures to the average retail trading measure in the previous 10 trading days. We use the ratio to reflect whether the stock is experiencing an intensive retail trading or not. By controlling the time-series trend, we focus on the relative retail trading activities, rather that the absolute level of retail trading activities.

In Table OA5, we present the retail trading activities around the S&P 500 index turnover days using the demeaned values. We estimate the average retail trading activities for each individual stock in the (-63,0) period before the effective day, and the adjust the corresponding variables by this average value to control for the individual stock level characteristics.

In Table OA6, we present the retail trading activities and stock return around the corporate Earnings Announcement days using the demeaned values. For each earnings announcement day, we estimate the average value during the (-20,20) window, and adjusted each variables by the corresponding means.

In Table OA7, we present the bi-variate portfolio sorting results with controlling for a set of stock characteristics. On each day, we first sort the stocks into decile groups based on the different stock characteristics, and then then sort stocks into finer decile groups based on the aggregate retail buying/selling orders. We then pool the portfolios together based on their rankings of retail trading measures to generate 10 portfolios that have similar stock characteristics. The realized returns of each portfolio in the following trading day are reported. The stock characteristics include the total order imbalance measure (Toi_LR) as in Lee and Ready (1991), stock return on the formation day (Return t), Stock return during the previous 21 trading days (STR21), idiosyncratic volatility during the previous 21 days (IVol21), the stock size (Mep), analyst following (NAna), and the analyst forecast dispersion (Disp).

Table OA1. Portfolio analysis based on order imbalance measure as in BJZZ (2020)

This table reports the average returns or alphas in bps and the corresponding t-statistics of decile portfolios sorted by the retail trading order imbalance measures: OIbjzz. Panel A and Panel B report the daily rebalanced portfolio and weekly rebalanced portfolio results. Excess return is the average returns in excess of the risk-free rate. Alpha is the intercept from the regression of daily excess returns on risk factors specified by an asset pricing model. The factor models include: the CAPM, the Fama-French three-factor model, and a four-factor model that includes Fama-French three factors and Carhart momentum factor. Long-Short return or Alpha is the return or alpha of a zero-cost portfolio that longs the high retail trading measure decile portfolio and shorts the low retail trading decile portfolio (i.e., H – L). The t-statistics shown in parentheses are computed based on standard errors with Newey-West corrections. ** and * indicate statistical significance at the 1% and 5% levels, respectively, using two-tailed tests. The sample period is from January 2010 to December 2016, covering total 1762 trading days.

Panel A: Daily decile portfolio based on aggregate retail trading orders imbalance (OIbjzz)

	Equal-weighted returns				Value-weighted returns			
	Excess Return	CAPM Alpha	3-factor Alpha	4-factor Alpha	Excess Return	CAPM Alpha	3-factor Alpha	4-factor Alpha
1 (Low)	2.54	-2.83	-2.29	-2.24	4.84	-0.46	-0.18	-0.17
	(1.01)	(-2.58)	(-4.20)	(-4.12)	(2.17)	(-0.61)	(-0.30)	(-0.29)
2	3.00	-2.95	-2.43	-2.34	4.60	-0.78	-0.63	-0.62
	(1.12)	(-2.92)	(-5.32)	(-5.28)	(2.15)	(-1.37)	(-1.27)	(-1.24)
5	5.44	-0.99	-0.55	-0.42	4.42	-1.06	-1.07	-1.09
	(1.91)	(-0.98)	(-0.95)	(-0.76)	(2.01)	(-2.65)	(-2.67)	(-2.71)
6	5.10	-1.31	-0.87	-0.72	5.32	-0.24	-0.24	-0.25
	(1.77)	(-1.33)	(-1.56)	(-1.40)	(2.37)	(-0.58)	(-0.59)	(-0.61)
9	11.67	5.57	6.08	6.21	7.49	2.05	2.16	2.19
	(4.19)	(5.29)	(10.91)	(11.73)	(3.42)	(3.49)	(3.89)	(3.92)
10 (High)	14.84	9.37	9.92	9.98	8.94	3.48	3.75	3.77
	(5.74)	(8.44)	(15.71)	(16.17)	(3.76)	(4.33)	(5.90)	(5.93)
H – L	12.29**	12.21**	12.21**	12.22**	4.10**	3.94**	3.92**	3.94**
(*t*-stat)	(18.71)	(18.73)	(18.76)	(18.79)	(4.89)	(4.75)	(4.71)	(4.72)

Panel B: Weekly decile portfolio based on aggregate retail trading orders imbalance (OIbjzz)

	Equal-weighted returns				Value-weighted returns			
	Excess Return	CAPM Alpha	3-factor Alpha	4-factor Alpha	Excess Return	CAPM Alpha	3-factor Alpha	4-factor Alpha
1 (Low)	16.00	-7.46	-4.10	-3.84	23.17	-0.63	0.82	0.74
	(1.52)	(-1.58)	(-1.75)	(-1.58)	(2.49)	(-0.18)	(0.30)	(0.26)
2	22.42	-5.52	-2.34	-1.83	24.02	-1.26	-0.63	-0.87
	(1.97)	(-1.29)	(-0.97)	(-0.76)	(2.65)	(-0.49)	(-0.27)	(-0.38)
5	25.95	-5.33	-2.58	-1.84	25.39	-0.74	-0.79	-0.68
	(2.09)	(-1.34)	(-1.11)	(-0.87)	(2.88)	(-0.46)	(-0.49)	(-0.41)
6	23.50	-8.24	-5.41	-4.80	24.51	-2.81	-2.75	-2.93
	(1.87)	(-1.96)	(-2.03)	(-1.86)	(2.60)	(-1.48)	(-1.49)	(-1.60)
9	39.82	9.97	13.09	13.84	31.35	6.44	6.92	7.15
	(3.25)	(2.39)	(4.98)	(5.24)	(3.38)	(2.12)	(2.30)	(2.37)
10 (High)	52.61	27.45	30.52	31.00	34.19	8.68	9.98	10.39
	(4.59)	(5.78)	(10.51)	(10.72)	(3.57)	(3.03)	(3.69)	(3.81)
H – L	36.62**	34.90**	34.63**	34.84**	11.02**	9.30**	9.16**	9.65**
(*t*-stat)	(11.49)	(11.44)	(11.38)	(11.68)	(3.47)	(2.83)	(2.80)	(2.92)

Table OA2. Daily Portfolio analysis based on all-but-non-micro stocks (Mep>NYSE Q20)

This table reports the average returns or alphas in bps and the corresponding t-statistics of daily rebalanced decile portfolios sorted by their corresponding retail trading measures: Rsel, Rbuy, and OIbjzz. **We exclude the micro-cap stocks whose market cap falls below the 20% breakpoint of the NYSE stocks**. Excess return is the average returns in excess of the risk-free rate. Alpha is the intercept from the regression of daily excess returns on risk factors specified by an asset pricing model. The factor models include: the CAPM, the Fama-French three-factor model, and a four-factor model that includes Fama-French three factors and Carhart momentum factor. Long-Short return or Alpha is the return or alpha of a zero-cost portfolio that longs the high retail trading measure decile portfolio and shorts the low retail trading decile portfolio (i.e., H – L). The t-statistics shown in parentheses are computed based on standard errors with Newey-West corrections. ** and * indicate statistical significance at the 1% and 5% levels, respectively, using two-tailed tests. The sample period is from January 2010 to December 2016, covering total 1762 trading days.

Panel A: decile portfolio based on aggregate retail selling orders (Rsel)

	Equal-weighted returns				Value-weighted returns			
	Excess Return	CAPM Alpha	3-factor Alpha	4-factor Alpha	Excess Return	CAPM Alpha	3-factor Alpha	4-factor Alpha
1 (Low)	8.09	2.10	2.56	2.64	8.66	2.97	3.22	3.27
	(3.15)	(2.45)	(5.84)	(6.17)	(3.70)	(4.03)	(5.52)	(5.61)
10 (High)	3.39	-3.53	-3.04	-2.92	4.37	-1.49	-1.49	-1.51
	(1.10)	(-2.92)	(-3.90)	(-3.87)	(1.85)	(-1.96)	(-1.98)	(-2.01)
H – L	-4.70**	-5.62**	-5.61**	-5.57**	-4.29**	-4.46**	-4.71**	-4.78**
(*t*-stat)	(-4.23)	(-5.39)	(-5.73)	(-5.68)	(-3.85)	(-3.93)	(-4.55)	(-4.60)

Panel B: decile portfolio based on aggregate retail buying orders (Rbuy)

	Equal-weighted returns				Value-weighted returns			
	Excess Return	CAPM Alpha	3-factor Alpha	4-factor Alpha	Excess Return	CAPM Alpha	3-factor Alpha	4-factor Alpha
1 (Low)	6.28	0.44	0.91	0.96	5.79	0.34	0.59	0.62
	(2.52)	(0.52)	(2.31)	(2.43)	(2.55)	(0.47)	(1.06)	(1.12)
10 (High)	4.61	-2.31	-1.84	-1.71	4.99	-0.67	-0.68	-0.66
	(1.48)	(-1.93)	(-2.22)	(-2.13)	(2.17)	(-0.93)	(-0.95)	(-0.93)
H – L	-1.67	-2.75*	-2.75**	-2.67**	-0.81	-1.01	-1.27	-1.29
(*t*-stat)	(-1.40)	(-2.53)	(-2.67)	(-2.61)	(-0.76)	(-0.93)	(-1.32)	(-1.34)

Panel C: decile portfolio based on aggregate retail trading orders imbalance (OIbjzz)

	Equal-weighted returns				Value-weighted returns			
	Excess Return	CAPM Alpha	3-factor Alpha	4-factor Alpha	Excess Return	CAPM Alpha	3-factor Alpha	4-factor Alpha
1 (Low)	5.45	-0.47	0.00	0.03	4.85	-0.43	-0.23	-0.22
	(2.19)	(-0.55)	(0.01)	(0.07)	(2.24)	(-0.69)	(-0.43)	(-0.41)
10 (High)	8.36	2.29	2.75	2.81	7.98	2.57	2.74	2.76
	(3.19)	(2.60)	(5.86)	(6.08)	(3.46)	(3.75)	(4.49)	(4.53)
H – L	2.91**	2.76**	2.75**	2.78**	3.13**	3.00**	2.97**	2.98**
(*t*-stat)	(5.52)	(5.38)	(5.34)	(5.45)	(4.30)	(4.14)	(4.08)	(4.09)

Table OA3. Hedge portfolio performance based on retail trading activates (year by year)

This table reports the average returns or alphas in bps and the corresponding t-statistics of daily rebalanced long-short hedge portfolio based on their corresponding retail buying and retail selling. **We divide the whole sample into 6 sub-samples, and report the results year by year.** Excess return is the average returns in excess of the risk-free rate. Alpha is the intercept from the regression of daily excess returns on risk factors specified by an asset pricing model. The factor models include: the CAPM, the Fama-French three-factor model, and a four-factor model that includes Fama-French three factors and Carhart momentum factor. The t-statistics shown in parentheses are computed based on standard errors with Newey-West corrections. ** and * indicate statistical significance at the 1% and 5% levels, respectively, using two-tailed tests. The sample period is from January 2010 to December 2016, covering total 1762 trading days.

Panel A: decile portfolio based on aggregate retail selling orders (Rsel)

	Equal-weighted returns				Value-weighted returns			
	Excess Return	CAPM Alpha	3-factor Alpha	4-factor Alpha	Excess Return	CAPM Alpha	3-factor Alpha	4-factor Alpha
Year 2010	-7.42*	-6.22	-5.37	-5.41	-4.24	-4.29	-4.36	-4.41
	(-2.36)	(-1.64)	(-1.43)	(-1.36)	(-1.25)	(-1.23)	(-1.28)	(-1.27)
Year 2011	-16.43**	-16.13**	-17.58**	-17.90**	-9.53*	-9.50*	-9.65*	-10.03*
	(-4.11)	(-3.66)	(-3.97)	(-4.03)	(-2.35)	(-2.34)	(-2.22)	(-2.39)
Year 2012	-10.79**	-10.25**	-10.29**	-10.13**	-13.28**	-13.38**	-12.95**	-12.79**
	(-3.09)	(-2.73)	(-2.71)	(-2.61)	(-3.82)	(-3.95)	(-3.78)	(-3.81)
Year 2013	-4.90	-4.05	-4.01	-4.00	-5.83	-6.31	-6.38	-6.25
	(-1.73)	(-1.45)	(-1.44)	(-1.45)	(-1.64)	(-1.86)	(-1.85)	(-1.85)
Year 2014	-10.01*	-9.60*	-9.65*	-9.55*	-7.79*	-8.20*	-6.89*	-6.89*
	(-2.27)	(-2.11)	(-2.12)	(-2.09)	(-2.17)	(-2.21)	(-2.14)	(-2.12)
Year 2015	-10.33**	-10.23**	-10.76**	-9.81**	-13.39**	-13.36**	-13.94**	-13.35**
	(-2.64)	(-2.60)	(-2.80)	(-3.02)	(-2.89)	(-2.89)	(-3.33)	(-3.22)
Year 2016	-13.49**	-12.69**	-10.57**	-10.65**	-9.42	-9.49	-7.76	-7.81
	(-3.24)	(-2.78)	(-2.65)	(-2.61)	(-1.66)	(-1.62)	(-1.47)	(-1.45)

Panel B: decile portfolio based on aggregate retail buying orders (Rbuy)

	Equal-weighted returns				Value-weighted returns			
	Excess Return	CAPM Alpha	3-factor Alpha	4-factor Alpha	Excess Return	CAPM Alpha	3-factor Alpha	4-factor Alpha
Year 2010	8.56*	9.39*	10.48*	10.43*	3.93	3.54	3.79	3.74
	(2.00)	(1.97)	(2.16)	(2.01)	(0.82)	(0.74)	(0.80)	(0.76)
Year 2011	0.85	1.07	-0.36	-0.57	-2.53	-2.66	-2.68	-2.82
	(0.22)	(0.25)	(-0.08)	(-0.13)	(-0.64)	(-0.66)	(-0.68)	(-0.72)
Year 2012	7.24*	7.70*	7.62*	7.98*	1.71	1.48	1.81	2.63
	(2.07)	(2.04)	(1.99)	(2.08)	(0.33)	(0.29)	(0.35)	(0.51)
Year 2013	12.68**	13.82**	13.80**	13.78**	7.21	5.71	5.64	5.82
	(4.22)	(4.38)	(4.37)	(4.40)	(1.56)	(1.17)	(1.13)	(1.15)
Year 2014	3.27	3.49	3.48	3.61	-0.38	-1.99	-0.69	-0.57
	(0.67)	(0.70)	(0.71)	(0.73)	(-0.08)	(-0.43)	(-0.16)	(-0.13)
Year 2015	1.90	1.98	1.57	2.63	-1.31	-1.39	-3.81	-3.39
	(0.49)	(0.50)	(0.40)	(0.87)	(-0.20)	(-0.23)	(-0.66)	(-0.59)
Year 2016	0.36	0.96	3.27	3.18	3.82	3.88	7.20	7.18
	(0.09)	(0.23)	(0.86)	(0.86)	(0.70)	(0.68)	(1.43)	(1.40)

Table OA4. Daily portfolio analysis based on demeaned retail trading measures

This table reports the average returns or alphas in bps and the corresponding t-statistics of daily rebalanced decile portfolios sorted by their corresponding retail trading measures: Rseldm, Rbuydm, and OIbjzzdm. **We adjust the retail trading measures by subtracting the average value in previous 10 trading days to control for the trend.** Excess return is the average returns in excess of the risk-free rate. Alpha is the intercept from the regression of daily excess returns on risk factors specified by an asset pricing model. The factor models include: the CAPM, the Fama-French three-factor model, and a four-factor model that includes Fama-French three factors and Carhart momentum factor. Long-Short return or Alpha is the return or alpha of a zero-cost portfolio that longs the high retail trading measure decile portfolio and shorts the low retail trading decile portfolio (i.e., H – L). The t-statistics shown in parentheses are computed based on standard errors with Newey-West corrections. ** and * indicate statistical significance at the 1% and 5% levels, respectively, using two-tailed tests. The sample period is from January 2010 to December 2016, covering total 1762 trading days.

Panel A: decile portfolio based on demeaned aggregate retail selling orders (Rseldm)

	Equal-weighted returns				Value-weighted returns			
	Excess Return	CAPM Alpha	3-factor Alpha	4-factor Alpha	Excess Return	CAPM Alpha	3-factor Alpha	4-factor Alpha
1 (Low)	12.38	7.52	8.00	8.09	7.76	2.37	2.74	2.75
	(4.40)	(4.91)	(6.95)	(7.14)	(2.92)	(1.79)	(2.57)	(2.59)
10 (High)	0.89	-4.48	-3.95	-3.82	2.51	-2.88	-2.68	-2.65
	(0.32)	(-3.30)	(-4.45)	(-4.38)	(1.10)	(-3.34)	(-3.40)	(-3.37)
H – L	-11.49**	-12.00**	-11.95**	-11.91**	-5.25**	-5.25**	-5.41**	-5.41**
(*t*-stat)	(-13.85)	(-14.25)	(-14.13)	(-14.02)	(-3.95)	(-3.96)	(-4.29)	(-4.28)

Panel B: decile portfolio based on demeaned aggregate retail buying orders (Rbuydm)

	Equal-weighted returns				Value-weighted returns			
	Excess Return	CAPM Alpha	3-factor Alpha	4-factor Alpha	Excess Return	CAPM Alpha	3-factor Alpha	4-factor Alpha
1 (Low)	3.03	-1.90	-1.42	-1.30	2.84	-2.71	-2.37	-2.29
	(1.07)	(-1.22)	(-1.26)	(-1.17)	(1.05)	(-2.20)	(-2.28)	(-2.22)
10 (High)	12.76	7.41	7.93	8.07	5.61	0.08	0.29	0.32
	(4.49)	(5.41)	(8.38)	(8.75)	(2.22)	(0.08)	(0.31)	(0.34)
H – L	9.73**	9.31**	9.35**	9.37**	2.77*	2.79*	2.66	2.61
(*t*-stat)	(10.29)	(9.81)	(9.72)	(9.73)	(1.99)	(1.99)	(1.94)	(1.91)

Panel C: decile portfolio based on demeaned aggregate retail trading orders imbalance (OIbjzzdm)

	Equal-weighted returns				Value-weighted returns			
	Excess Return	CAPM Alpha	3-factor Alpha	4-factor Alpha	Excess Return	CAPM Alpha	3-factor Alpha	4-factor Alpha
1 (Low)	3.70	-1.78	-1.24	-1.18	5.38	-0.12	0.17	0.19
	(1.42)	(-1.58)	(-2.24)	(-2.13)	(2.32)	(-0.16)	(0.31)	(0.33)
10 (High)	12.22	6.85	7.40	7.47	8.03	2.55	2.84	2.84
	(4.81)	(6.31)	(13.11)	(13.48)	(3.34)	(3.39)	(5.18)	(5.16)
H – L	8.52**	8.63**	8.63**	8.64**	2.64**	2.67**	2.67**	2.65**
(*t*-stat)	(13.96)	(14.19)	(14.23)	(14.21)	(3.51)	(3.52)	(3.54)	(3.52)

Table OA5. Retail Trading Activities around S&P 500 index addition and deletion (demeaned value, table 10)

This table shows the time-series average of daily stock returns and retail trading activities around the S&P 500 index addition or deletion. EDay is defined as the effective addition/deletion day, which is Day 0. We focus on a window of 5 weeks (25 trading days) before and 4 week (20 trading days) after the effective day. Daily stock returns and the retail trading activates around the EDay are reported. Dvol is the average daily trading volume. Rbuy is the daily aggregate retail buying orders. Rsel is the aggregate retail selling orders. Rimb is the net retail buying orders, defined as Rbuy-Rsel. **We adjust all the trading measures by the average value in (-63,0) window**. The t-statistics shown in parentheses are computed based bootstrap method with 10,000 iterations.

Panel A: Retail trading activities around the S&P500 index addition day

	(-25,-21)	(-20,-16)	(-15,-11)	(-10,-6)	(-5,-3)	-2	-1	EDay	1	2	(3,5)	(6,10)	(11,15)	(16,20)
Dvol($B)	-0.05**	-0.06**	-0.05**	-0.03	0.06**	1.93**	0.10**	0.00	-0.01	-0.01	-0.03	-0.03*	-0.07**	-0.07**
Rsel(%)	0.09	0.05	-0.09	0.06	-0.17*	-0.49**	-0.63	-0.50**	-0.30*	-0.38**	-0.23**	-0.17*	-0.21**	-0.16*
Rbuy(%)	-0.00	0.10	0.01	0.03	-0.15	-0.47**	-1.07**	-0.48**	-0.26	-0.31**	-0.20*	-0.25**	-0.22**	-0.21**
Rimb(%)	-0.07	0.05	0.10	-0.05	0.02	0.02	-0.36	0.02	0.05	0.07	0.03	-0.09	-0.01	-0.04
(*t*-stat)	(-0.60)	(0.63)	(1.70)	(-0.62)	(0.25)	(0.19)	(-1.25)	(0.19)	(0.30)	(0.60)	(0.39)	(-1.27)	(-0.10)	(-0.75)
Return(‱)	14.61	16.69	14.15	17.03*	15.52	-7.51	-33.14*	3.69	-3.48	9.58	-29.21*	15.86	1.55	21.38**
(*t*-stat)	(1.69)	(1.52)	(1.37)	(1.99)	(0.96)	(-0.38)	(-1.97)	(0.13)	(-0.17)	(0.49)	(-2.38)	(1.70)	(0.19)	(2.85)
ExRet(‱)	6.66	21.06	8.37	12.37	12.07	-13.23	-53.95**	-1.19	1.46	-2.54	-23.63*	-0.05	-6.42	9.00
(*t*-stat)	(0.89)	(1.94)	(0.93)	(1.64)	(0.85)	(-0.80)	(-3.08)	(-0.05)	(0.09)	(-0.16)	(-2.35)	(-0.01)	(-0.90)	(1.37)

Panel B: Retail trading activities around the S&P500 index deletion day

	(-25,-21)	(-20,-16)	(-15,-11)	(-10,-6)	(-5,-3)	-2	-1	EDay	1	2	(3,5)	(6,10)	(11,15)	(16,20)
Dvol($B)	-0.00	-0.00	0.00	0.00	0.01	0.05**	0.48**	0.04**	0.01*	0.01*	-0.00	-0.01	-0.00	0.01
Rsel(%)	0.12	-0.04	0.06	0.15	-0.18	-0.32	-0.16	-0.80**	-0.14	0.14	-0.01	0.20	-0.15	-0.04
Rbuy(%)	-0.05	-0.12	0.19*	0.27	-0.23	-0.53**	-0.36	-1.11**	-0.18	0.10	-0.03	0.11	0.07	-0.04
Rimb(%)	-0.16	-0.08	0.13	0.08	-0.04	-0.20	-0.19	-0.31*	-0.04	-0.03	-0.05	-0.08	0.23*	-0.00
(*t*-stat)	(-1.66)	(-0.94)	(1.46)	(0.42)	(-0.33)	(-0.79)	(-0.98)	(-2.08)	(-0.22)	(-0.12)	(-0.25)	(-0.70)	(2.55)	(-0.01)
Return(‱)	-11.99	-21.41	45.83*	2.18	-20.78	55.74	17.48	55.75	-9.73	82.80*	2.56	15.82	-16.51	37.68*
(*t*-stat)	(-0.74)	(-1.20)	(2.47)	(0.14)	(-1.16)	(1.42)	(0.59)	(1.66)	(-0.23)	(1.97)	(0.12)	(0.99)	(-0.98)	(2.30)
ExRet(‱)	-16.19	-14.95	25.42	-5.75	-21.12	41.20	18.19	44.09	-10.43	59.84	-6.01	5.49	-20.66	30.79
(*t*-stat)	(-1.05)	(-1.08)	(1.53)	(-0.43)	(-1.28)	(1.14)	(0.63)	(1.40)	(-0.26)	(1.68)	(-0.31)	(0.36)	(-1.36)	(1.84)

Table OA6. Portfolio return and individual trading around the Earnings Announcement day (demeaned value, table 12)

This table presents analysis of stock returns and individual trading activists around earnings announcement days. In each quarter, we estimate the stocks' standard earning announcement surprise (SUE) based on the actual EPS and the analyst census EPS in previous month, and then rank stocks into 1 of the 5 quintiles according to their SUE measure. We report the time-series average of the portfolio return and the associated retail trading measures during the (-20, 20) window. Panel A, B, and C report the results for highest SUE (Q5), middle SUE (Q3), and lowest SUE (Q1). **We adjust all the trading measures by the average value in (-20, 20) window**. The t-statistics shown in parentheses are computed based on standard errors with Newey-West corrections.

	Day (-20,-16)	Day (-15,-11)	Day (-10,-6)	Day (-5,-3)	Day (-2)	Day (-1)	EADay (0)	Day (1)	Day (-2)	Day (3,5)	Day (6,10)	Day (11,15)	Day (15,20)
Panel A: Earnings announcement with extreme positive earnings surprise, ranked in Q5 (Top 20%)													
Dvol($M)	-2.66**	-3.17**	-3.08**	-2.78**	-1.33**	5.87**	38.65**	12.09**	4.87**	2.05**	-0.36	-1.36**	-1.60**
Rsel(%)	-0.04	-0.05	-0.05	-0.09*	-0.18**	-0.12**	-0.05	0.26**	0.16**	0.08**	0.03	0.03	0.06
Rbuy(%)	-0.06	-0.02	-0.01	0.02	0.19**	0.61**	0.05	0.06	-0.08	-0.07**	-0.01	-0.01	-0.04
Rimb(%)	-0.02	0.03	0.04**	0.10**	0.36**	0.72**	0.10*	-0.21**	-0.23**	-0.15**	-0.04*	-0.03	-0.09**
(*t*-stat)	(-0.92)	(0.91)	(3.68)	(2.85)	(8.58)	(15.09)	(2.41)	(-5.09)	(-5.93)	(-5.23)	(-2.47)	(-1.42)	(-5.07)
Return(‱	16.03**	13.69**	11.48*	7.35	7.93	35.22**	321.93**	19.35*	10.05	10.57	3.27	9.96*	9.53**
(*t*-stat)	(3.08)	(3.27)	(2.48)	(1.35)	(1.46)	(6.00)	(25.36)	(2.16)	(1.41)	(1.64)	(0.39)	(2.08)	(3.39)
ExRet(‱)	6.01	3.84	2.31	1.52	6.61*	34.56**	320.21**	15.21*	2.98	10.03*	3.69	5.77	4.75
(*t*-stat)	(1.94)	(1.12)	(0.54)	(0.30)	(2.09)	(6.07)	(25.17)	(2.71)	(0.74)	(2.67)	(1.06)	(1.86)	(1.94)
Panel B: Earnings announcement with moderate earnings surprise, ranked in Q3 (middle 20%)													
Dvol($M)	-8.99**	-8.89**	-8.54**	-4.87**	-0.39	24.92**	140.62**	39.66**	15.52**	3.59**	-4.20**	-5.43**	-8.10**
Rsel(%)	0.01	-0.03	-0.04	-0.09**	-0.11**	-0.01	0.20*	0.15**	0.10**	0.02*	0.01	0.00	0.00
Rbuy(%)	0.00	-0.02	-0.03	-0.05**	0.02	0.35**	0.20**	0.11**	0.02	-0.02*	-0.02	-0.02	-0.02
Rimb(%)	-0.01	0.01	0.02	0.04**	0.13**	0.36**	-0.00	-0.05**	-0.09**	-0.04**	-0.04**	-0.03	-0.02
(*t*-stat)	(-0.64)	(0.94)	(0.80)	(3.11)	(7.75)	(9.69)	(-0.14)	(-3.17)	(-4.78)	(-3.99)	(-2.90)	(-1.72)	(-1.55)
Return(‱	6.52	8.39**	8.80**	10.14**	3.89	11.22**	38.60**	7.99**	3.91	0.56	4.38	5.77	7.15**
(*t*-stat)	(1.44)	(2.79)	(5.45)	(3.55)	(1.39)	(3.25)	(5.36)	(2.90)	(1.06)	(0.14)	(0.88)	(1.24)	(3.56)
ExRet(‱)	0.39	-0.10	0.23	2.48	1.29	8.77**	32.47**	2.05	-3.54*	0.86	3.52**	2.34	2.94*
(*t*-stat)	(0.28)	(-0.09)	(0.18)	(1.14)	(0.54)	(5.35)	(5.92)	(1.26)	(-2.40)	(0.77)	(3.50)	(1.75)	(2.48)
Panel C: Earnings announcement with extreme negative earnings surprise, ranked in Q1 (Bottom 20%)													
Dvol($M)	-1.36**	-1.69**	-1.54**	-1.29**	-0.37	3.46**	28.41**	7.80**	3.26**	0.67**	-0.60**	-1.42**	-2.05**
Rsel(%)	0.00	-0.02	0.02	-0.07	-0.07*	-0.03	-0.17	0.26*	0.03	-0.06**	0.03	0.02	0.02
Rbuy(%)	-0.05	0.04	0.03	0.03	0.18**	0.45**	-0.13	0.03	-0.03	-0.08**	-0.03	-0.00	-0.05*
Rimb(%)	-0.05	0.06*	0.01	0.10**	0.25**	0.46**	0.04	-0.21**	-0.07	-0.01	-0.07*	-0.02	-0.07**
(*t*-stat)	(-1.92)	(2.47)	(0.40)	(4.02)	(7.11)	(6.96)	(0.80)	(-2.83)	(-1.37)	(-0.73)	(-2.16)	(-1.97)	(-3.26)
Return(‱	9.10	5.90	0.29	-4.53	-13.28	-23.27**	-352.90**	-43.06**	-21.01**	-1.35	2.75	9.74*	4.37
(*t*-stat)	(1.74)	(1.29)	(0.06)	(-1.09)	(-2.03)	(-2.86)	(-33.69)	(-3.28)	(-3.73)	(-0.19)	(0.35)	(2.73)	(1.39)
ExRet(‱)	-1.07	-4.34	-8.43	-9.21*	-12.88**	-23.65**	-353.52**	-47.22**	-27.03**	-1.41	2.79	4.97*	-1.03
(*t*-stat)	(-0.32)	(-1.18)	(-1.96)	(-2.48)	(-4.56)	(-5.39)	(-41.34)	(-5.22)	(-10.66)	(-0.33)	(0.76)	(2.09)	(-0.34)

Table OA7. Bi-variate sorted portfolio analysis with controlling of other characteristics

This table reports the average returns and four-factor alphas of decile portfolios sorted by their retail trading activities after first sorting on some typical stock characteristics, including total order imbalance by Lee and Ready (1991) (Toi_LR), return of previous day (Ret(t)), return in previous 21 trading days (STR21), idiosyncratic volatility in previous 21 trading days (IVol21), market cap in previous day (Mep), number of analyst following (NAna), and analyst forecast dispersion (Disp). Panel A and B report the results for aggregate retail selling orders (Rsel) and aggregate retail buying orders (Rbuy) respectively. Long-Short return or Alpha is the return or alpha of a zero-cost portfolio that longs the high decile portfolio and shorts the low decile portfolio (i.e., H – L or FF4 Alpha). The t-statistics shown in parentheses are computed based on standard errors with Newey-West corrections. ** and * indicate statistical significance at the 1% and 5% levels, respectively, using two-tailed tests. To save space, we only report the results for the 1st, 2nd, 5th, 6th, 9th, and 10th decile portfolios.

Panel A: Aggregate retail selling orders (Rsel)

	Equal-weighted returns							Value-weighted returns						
	Toi_LR	Ret (t)	STR21	IVol21	Mep	NAna	Disp	Toi_LR	Ret (t)	STR21	IVol21	Mep	NAna	Disp
1 (Low sell)	9.97	10.09	10.24	10.55	10.45	9.29	8.92	8.69	8.46	8.69	8.70	7.61	7.99	8.34
2	8.25	7.64	8.58	8.43	9.37	8.26	8.02	6.68	6.42	7.27	7.22	6.61	6.76	7.26
5	7.15	7.61	7.13	7.26	7.18	6.76	6.35	5.45	5.86	6.04	6.07	6.22	6.14	5.72
6	7.01	7.73	7.47	6.11	6.58	6.87	5.87	5.56	5.77	5.62	5.36	5.46	4.98	5.60
9	5.15	3.99	4.55	3.87	2.95	4.04	5.49	4.76	3.79	3.44	3.79	3.66	3.67	3.93
10 (High sell)	-0.45	-0.67	-0.09	2.82	0.92	-0.32	-0.19	2.99	2.22	1.53	5.45	4.45	4.76	3.46
H – L	-10.42**	-10.76**	-10.32**	-7.73**	-9.53**	-9.61**	-9.11**	-5.70**	-6.24**	-7.16**	-3.24*	-3.16**	-3.23**	-4.88**
(*t*-stat)	(-6.69)	(-8.31)	(-7.55)	(-7.88)	(-8.50)	(-6.17)	(-6.71)	(-3.19)	(-3.88)	(-4.08)	(-2.40)	(-3.13)	(-2.75)	(-3.78)
FF4 Alpha	-10.10**	-9.85**	-9.29**	-6.44**	-10.19**	-10.26**	-9.36**	-6.53**	-6.48**	-7.65**	-3.22**	-3.61**	-3.80**	-5.04**
(*t*-stat)	(-6.21)	(-7.10)	(-6.34)	(-6.32)	(-9.64)	(-6.92)	(-6.94)	(-3.85)	(-4.12)	(-4.58)	(-2.97)	(-3.72)	(-3.42)	(-4.61)

Panel B: Aggregate retail buying orders (Rbuy)

	Equal-weighted returns							Value-weighted returns						
	Toi_LR	Ret (t)	STR21	IVol21	Mep	NAna	Disp	Toi_LR	Ret (t)	STR21	IVol21	Mep	NAna	Disp
1 (Low buy)	6.18	5.89	6.52	5.99	6.06	6.49	6.49	5.68	5.21	5.83	5.68	6.03	6.02	5.84
2	5.90	5.94	6.33	6.18	6.32	6.20	6.32	6.06	5.83	6.41	6.13	5.76	6.03	6.51
5	6.41	6.62	6.45	5.76	5.99	6.26	5.97	5.23	6.40	5.37	5.50	5.21	5.23	5.95
6	6.25	6.22	6.35	5.45	5.67	5.92	6.62	5.47	4.72	5.33	5.12	5.40	5.66	5.74
9	7.18	5.93	5.04	7.44	7.30	5.41	5.77	5.41	5.19	5.32	5.22	5.08	5.05	5.58
10 (High buy)	7.81	10.84	11.35	12.56	8.21	6.66	6.28	6.80	6.95	6.15	5.88	5.32	5.41	5.32
H – L	1.63	4.96**	4.84**	6.57**	2.14	0.17	-0.21	1.12	1.74	0.32	0.20	-0.72	-0.62	-0.52
(*t*-stat)	(1.06)	(3.91)	(3.50)	(6.81)	(1.86)	(0.10)	(-0.14)	(0.62)	(1.11)	(0.17)	(0.16)	(-0.75)	(-0.56)	(-0.45)
FF4 Alpha	1.96	5.69**	5.71**	7.50**	1.37	-0.27	-0.46	0.05	1.19	-0.33	0.14	-1.31	-1.19	-0.70
(*t*-stat)	(1.28)	(4.20)	(3.78)	(7.37)	(1.41)	(-0.19)	(-0.35)	(0.03)	(0.76)	(-0.19)	(0.14)	(-1.51)	(-1.19)	(-0.71)