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Resolving a Paradox: Retail Trades Positively Predict Returns but Are Not Profitable

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Abstract

Retail order imbalance positively predicts returns, but on average retail investor trades lose money. Why? Order imbalance tests equal-weighted stocks, but retail purchases concentrate on attention-grabbing stocks that subsequently underperform. Long–short strategies based on extreme quintiles of retail order imbalance earn dismal annualized returns of −14.8% among stocks with heavy retail trading but earn 6.6% among other stocks. Our results reconcile the literatures on the performance of retail investors, the predictive content of retail order imbalance, and attention-induced trading and returns. Smaller retail trades concentrate more on attention-grabbing stocks and perform worse.

I. Introduction

At short horizons, retail investors lose money through trading. At short horizons, the order imbalance of retail investors positively predicts future returns. Both seemingly contradictory statements about retail investors are well established. Several studies of retail investors (using a variety of data sets and methods) show that on average retail investors earn poor returns at short horizons, for example, less than a month, as well as longer horizons (Odean (1999), Barber and Odean (2000), (2001), Grinblatt and Keloharju (2000), Chen, Kim, Nofsinger, and Rui (2007), Barber, Lee, Liu, and Odean (2009), and Jones, Shi, Zhang, and Zhang (2020)). In contrast, several studies of retail investors (using a variety of data sets and methods) show that retail order imbalance positively predicts future returns at short horizons (Barber, Odean, and Zhu (2008), Hvidkjaer (2008), Kaniel, Saar, and Titman (2008), Kaniel, Liu, Saar, and Titman (2012),

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Kelley and Tetlock (2013), Barrot, Kaniel, and Sraer (2016), and Boehmer, Jones, Zhang, and Zhang (2021)).[1]

Given this seemingly conflicting evidence, articles reach different conclusions about the profitability of retail trades. Odean ((1999), p. 1296) finds that "even when trading costs are ignored, these investors actually lower their returns through trading." Grinblatt and Keloharju ((2000), p. 66) write that "the least sophisticated investors (households)… generate the worst performance." And Barber, Lee, Liu, and Odean ((2008), p. 609) conclude that "individual investor trading results in systematic and economically large losses."

In contrast, many order imbalance articles interpret the positive correlation between retail order imbalance and short-term future returns as evidence that retail investors profit from trading. Kaniel, Saar, and Titman ((2008), p. 273) propose that retail order imbalance forecasts returns because individuals "provide liquidity to meet institutional demand for immediacy" leading to retail investor profits at horizons of 20 days or longer. Kaniel, Liu, Saar, and Titman ((2012), p. 677) interpret the ability of retail order imbalance to predict returns around earnings announcements as "evidence of informed individual investor trading" and of liquidity provision.[2] Boehmer, Jones, Zhang, and Zhang ((2021), p. 2249) begin their article with the following question: "Can retail equity investors predict future stock returns, or do they make systematic costly mistakes in their trading decisions?" The question implies that these outcomes exclude each other. We find that both are true. Over short horizons, retail order imbalance positively predicts future returns but retail investors lose by trading.

The intuition for our result that reconciles the seemingly contradictory evidence on the performance of retail investors can be illustrated with a simple example. Suppose an investor purchases \$1,000 of stock A, \$1,000 of stock B, and \$3,000 of stock C. Over the next week, stocks A and B earn an abnormal returns of 1% and stock C earns an abnormal return of −1%. If this trading behavior and outcome were persistent weeks after week, then an equal-weighted strategy that purchases the same three stocks as the investor would earn 33 bps a week $\left(\frac{1\%+1\%-1\%}{3}\right)$. However, the investor would lose 20 bps a week $\left(\frac{(\$1{,}000\times 1\%+\$1{,}000\times 1\%-\$3{,}000\times 1\%)}{\$5{,}000}\right)$. The investor's buying activity would positively predict stock returns in the cross section, but the investor's portfolio would lose money.

Like the trades of the hypothetical investor in our three-stock example, the trades of retail investors positively predict returns if one weights each stock equally, but the trades actually lose money. This is because the stocks that retail investors

[1]At longer horizons, there is evidence that retail order imbalance negatively predicts returns (Barber, Odean, and Zhu (2008), Hvidkjaer (2008)). The focus of this article is the conflicting results at short horizons.

[2]In contrast to the liquidity and information explanations, Barber, Odean, and Zhu (2008) argue temporary price pressure can lead to the observed positive correlation between retail order imbalance and returns. They document that retail order imbalance is positively serially correlated and argue that order imbalance positively predicts short-term returns because it predicts price pressure. This hypothesis does not necessarily imply that retail investors earn positive short-term returns, because they themselves are the buyers (sellers) at the temporarily high (low) prices they create.

trade most actively underperform. Furthermore, the underperformance of stocks intensely purchased by retail investors manifests both on the following days and on the day of the trade itself.

Our empirical analysis is based on U.S. retail trades, which we identify in the Trades and Quote (TAQ) data set from 2010 to 2019 using the price improvement algorithm described in Boehmer, Jones, Zhang, and Zhang (2021). Previous studies of the predictability of order flow and the performance of retail investors analyze a wide variety of data sets. Thus, some of the differences in findings could be due to differing data. In this article, we reconcile the disparate findings with a single data set.

To simply illustrate our main finding, we construct long–short portfolios based on retail standardized order imbalance (SOI) but crucially condition the strategies on the intensity of retail trading.[3] Specifically, we first sort stocks into quintiles of retail order imbalance on day *t*. We then sort the stocks within each order imbalance quintile into deciles of standardized abnormal retail trading volume (SARV).[4] Figure 1 shows how retail investors perform badly with the stocks they trade most actively. The figure presents returns for the 5 days after the day of trade for stocks heavily bought (top quintile of standardized retail order imbalance, Graph A), stocks heavily sold (bottom quintile, Graph B), and for long–short strategies (long top quintile and short bottom quintile, Graph C). Note that stocks are equal-weighted in both strategies. In each graph, the returns are separately depicted for stocks in the top decile of SARV (red lines, circle markers) versus other stocks (black lines, triangle markers). Among stocks bought (top order imbalance quintile, Graph A), returns are dismal on stocks in the highest SARV decile; in contrast, returns are slightly positive for stocks in the bottom 9 SARV deciles. Among stocks sold (bottom order imbalance quintile, Graph B), the result is reversed though less pronounced. Stocks in the top SARV decile outperform those in the bottom 9 SARV deciles. In Graph C, we summarize the returns to long–short trading strategies that condition on the level of retail volume. For stocks in the top SARV decile the long–short strategy loses 29.4 basis points over 5 days (an annualized return of −14.8%). For other stocks, it earns 13.0 basis points over 5 days (an annualized return of 6.6%).

These results highlight the importance of weighting schemes in the analysis of investment strategies. To further underscore this point, we construct long–short investment strategies that buy all stocks in the top quintile of retail order imbalance and short all stocks in the bottom quintile but vary the weighting of stocks. In the

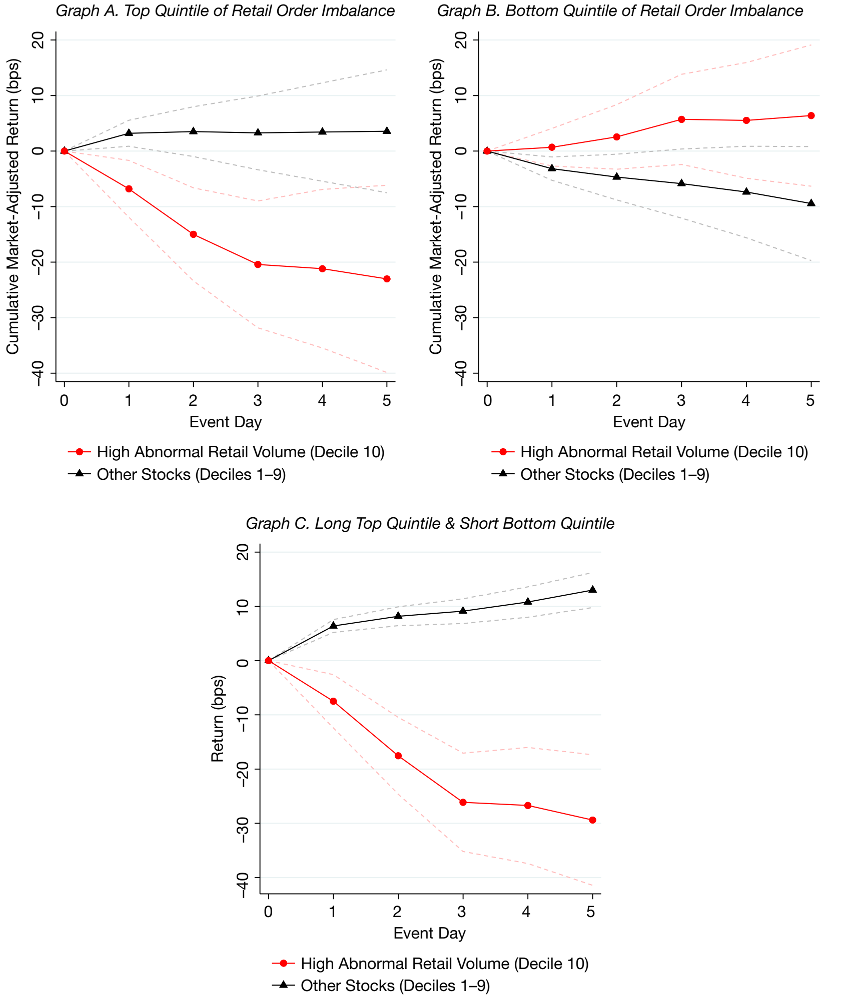
[3]Standardized order imbalance for a stock is the stock's retail order imbalance less the market-wide retail order imbalance divided by the standard deviation of the stock's retail order imbalance. The adjustment of standard deviation has the effect of deflating order imbalances that are measured using few trades. We prefer standardized order imbalance to simple order imbalance measures (e.g., buys less sells divided by buys plus sells) because without standardization the stocks that appear in extreme retail order imbalance quintiles tend to be small stocks with few trades. Our results are similar if we use the unstandardized measures but the economic significance of trading in the extreme order imbalance quintiles is smaller.

[4]Standardized abnormal retail volume (SARV) on day *t* as the difference between observed retail volume on day *t* and its recent average (from $t-45$ to $t-6$) scaled by the standard deviation of retail volume over the same 40-day period.

FIGURE 1

Cumulative Market-Adjusted Returns on Stocks in Extreme Retail Order Imbalance Quintiles Conditional on Retail Volume

Figure 1 depicts the cumulative market-adjusted returns in event time after the close on day 0 for the average stock in the top quintile of standardized retail order imbalance (Graph A) and bottom quintile of retail order imbalance (Graph B) conditional on the level of abnormal retail volume. Graph C plots the returns to a long–short strategy of buying stocks in the top quintile and selling stocks in the bottom quintile. In each graph, returns based on stocks in the top decile of standardized abnormal retail volume are shown in red with circle markers; returns on all other stocks are shown in black with triangle markers. Dashed lines represent 95% confidence intervals.



benchmark strategy, stocks are weighted equally, and the long–short strategy earns an impressive 6.6% annually ($p < 0.01$), which leaves the mistaken impression that retail investors are engaging in profitable trades. However, when stocks in the top (bottom) quintile are weighted by the value of buys (sells), the long–short strategy earns a dismal −5.1% annually ($p < 0.01$). When stocks in the top (bottom) quintile are weighted by the number of buys (sells), the long–short strategy performs even worse (earning −14.5% annually ($p < .01$)). It is worth emphasizing that these three long–short portfolios buy exactly the same stocks and short exactly the same stocks (only the weighting of stocks differ). Thus, weighting long–short portfolios by the return on the average stock, average dollar traded, or average number of trades yields dramatically different conclusions regarding the profitability of strategies based on retail order imbalance.

Figure 1 shows that retail investors lose money on stocks that they heavily buy on the days following the trade. Most order imbalance studies sort stocks on the day of trade and calculate subsequent returns. Many of these studies do not examine day of trade returns.[5] In additional analyses, we show that same-day trading losses are largely concentrated in stocks with high abnormal retail trading volume and a high-order imbalance. Figure 2 plots the purchased-weighted return on the day of sale and the effective spread, which compares the purchase price to the midpoint of the bid–ask spread at the time of trade, for SOI quintiles.[6] As in Figure 1, the results are plotted separately for stocks in the bottom 9 SARV deciles (Graph A) and those in the highest SARV decile (Graph B). Most trades result in same-day losses that are less than the bid–ask spread. However, for trades in the highest SARV decile and highest order imbalance quintile, the same-day losses are over *four* times as great as the bid–ask spread (see the rightmost bars in Graph B of Figure 2). Thus, on the day of trade and on subsequent days, retail investors lose the most trading stocks with high abnormal trading volume and a high-order imbalance.

It is worth noting that our return analysis is restricted to short horizons. Furthermore, the same-day losses we document do not include commissions. Other articles have shown that retail investors underperform over long horizons and that commissions contribute to their overall underperformance (Barber and Odean (2000), Barber, Zhu, and Odean (2008), Hvidkjaer (2008), and Barber, Lee, Liu, and Odean (2009)).

The main message to emerge from our empirical analysis is that there is an important interaction between the returns earned on retail trades and the intensity of retail trading. In contrast to prior findings that document retail order imbalance positively predicts returns, we show retail order imbalance negatively predicts returns for stocks with high levels of retail trading. The prior findings and our results raise two distinct questions: i) why do retail trades positively predict short-term returns when retail volume is not unusually high? and ii) why do retail trades negatively predict short-term returns when retail volume is unusually high? The first question is the focus of Boehmer, Jones, Zhang, and Zhang (2021), which

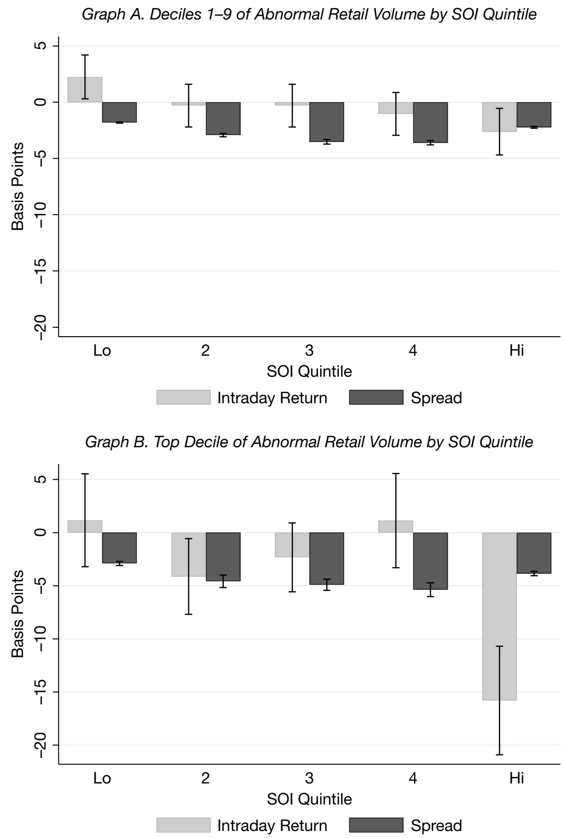
[5]Some studies note spreads or same-day losses may not offset the apparent gains from order imbalance strategies. For example, Barrot, Kaniel, and Sraer (2016) analyze trades by 91,647 French retail investors and find that day of trade losses are enough to offset subsequent gains for trading strategy based on order imbalance. Linnainmaa (2010) finds that investors on the Helsinki Stock Exchange earn same-day losses, on average, on market orders. Kelly and Tetlock (2013) find that same-day order imbalance positively predicts returns but not by enough to offset the cost of spreads.

[6]We measure the effective spread using the ratio of the mean trade price to the mean midpoint of the bid–ask spread; both means are purchase-weighted across all trades on each calendar day and then averaged across days. Standard errors are based on the time-series standard deviation of the daily means. Figure A2 in the Supplementary Material presents a similar analysis for sales and finds similar patterns. Note that the comparison of buy and sell returns within a particular partition or order imbalance and abnormal retail volume is misleading because buying is more concentrated in the top order imbalance quintile (SOI 5) than is selling.

FIGURE 2

Trading Day Returns on Retail Purchases by Quintiles of Retail Order Imbalance Conditional on Retail Volume

Figure 2 presents the mean daily purchase-weighted return on stocks bought by retail investors (gray bars) and the one-way estimated spread (black bars) for each quintile of standardized retail order imbalance (horizontal axis). Graph A presents results for stocks in the bottom 9 deciles of abnormal retail volume. Graph B presents the results for stocks in the top decile of abnormal retail volume.



develops the methodology that we use to identify retail trades (hereafter BJZZ). They consider three potential explanations for why retail order imbalance positively forecasts short-term returns: persistence in retail order flow, liquidity provision, and informed trading. They conclude that persistent order flow and liquidity provision account for about half of the positive predictive power of retail order imbalance and informed trading accounts for the rest.[7]

[7]Barardehi, Bernhardt, Da, and Warachka (2021) show that wholesalers internalize more order flow when institutional demand is high. Thus, the BJZZ measure of retail order imbalance is negatively correlated with institutional demand. As a result, the positive relationship between retail order flow as measured by BJZZ and short-term returns may be driven by a negative relationship between institutional demand and short-term returns.

In contrast to BJZZ, we show that retail trades negatively predict short-term returns when retail volume is unusually high and ask why. We argue that attention-induced buying can explain the concentrated underperformance of retail investors (Barber and Odean (2008)). Retail investors will be on the buy side of the market for attention-grabbing stocks because when picking a stock to buy the opportunity set includes all stocks in the market but when selling retail investors tend to sell what they own (i.e., refrain from short selling). In theory, stocks more heavily bought by attention-driven investors underperform (Barber and Odean (2008)). Using three proxies for investor attention (volume, extreme returns, and news), we show that retail buying is concentrated in these attention-grabbing stocks. Importantly, these attention-grabbing stocks earn dismal returns dragging down the overall return earned by retail investors.

Consistent with this narrative, the stocks with the biggest increase in users on the popular Robinhood app tend to earn poor returns (Barber, Huang, Odean, and Schwarz (2022)). Similarly, several studies document price reversals following attention-grabbing events: Jim Cramer's stock recommendations (Keasler and McNeil (2010), Bolster, Trahan, and Venkateswaran (2012), Engelberg, Sasseville, and Williams (2012)), the WSJ Dartboard Column (Barber and Loeffler (1993), Liang (1999)), Google stock searches (Da, Engelberg, and Gao (2011), Da, Hua, Hung, and Peng (2022)), and repeat news stories (Tetlock (2011)). Barber, Lin, and Odean (2021) discuss the role of media in directing investor attention. We contribute to this literature by documenting that stocks with a combination of high retail order imbalance and abnormal retail volume (ARV) earn dismal returns. Furthermore, a large proportion of all retail buying is concentrated in these stocks, which explains why (when equal-weighted) retail trading can positively predict returns but (when weighted by dollars traded or the number of trades) retail trading is unprofitable.

In additional analyses, we use trade size as a proxy for investor sophistication because trade size is correlated with wealth, income, and self-reported measures of investment experience and knowledge in brokerage data. We conjecture that less sophisticated investors will place more attention-based trades than other retail investors and will perform worse. Consistent with our conjecture, we show small trades are more concentrated in attention-grabbing stocks, which we identify using three proxies for attention (volume, extreme returns, and abnormal news coverage). Moreover, we show small trades perform worse than large trades. This evidence adds to the accumulating evidence that less sophisticated investors suffer the biggest trading losses (Barber and Odean (2000), Grinblatt and Keloharju (2000), Li, Geng, and Subramanyam (2017), Campbell, Ramadorai, and Ranish (2019), Jones, Shi, Zhang, and Zhang (2020), and Eaton, Green, Roseman, and Wu (2022)).

In summary, our analysis reconciles two well-established yet seemingly contradictory facts about equity markets: i) retail order imbalance positively predicts short-term returns, and ii) on average, retail investors lose money over the short-term by trading. The reconciliation of these facts can be traced to the strong interaction between the level of retail trading and the returns on order imbalance strategies. We show that the concentration of trading in the stocks that

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subsequently underperform means that on average retail investors lose from trade. The concentration of retail buying in underperforming stocks is consistent with the literature that documents investors earn predictably poor returns following attention-grabbing events (Barber and Loeffler (1993), Liang (1999), Keasler and McNeil (2010), Da, Engelberg, and Gao (2011), Tetlock (2011), Bolster, Trahan, and Venkateswaran (2012), Engelberg, Sasseville, and Williams (2012), Barber, Huang, Odean, and Schwarz (2022), and Da, Hua, Hung, and Peng (2022)). Prior studies have hypothesized that retail order imbalance positively predicts short-term returns because retail investors are informed or profit from providing liquidity. While some retail investors are undoubtedly informed and some may profit from providing liquidity, most retail investors lose money through trading in the short term just as they do in the long term.

II. Data and Methods

In this section, we describe the TAQ data set, the algorithm we use to identify retail trades, and the main variables used in our empirical analysis.

A. Data

We identify retail transactions from TAQ from 2010 to 2019 using a methodology developed and described in BJZZ. BJZZ document that most U.S. stock trades initiated by retail investors do not take place on registered exchanges. The retail trades placed by wholesalers or via broker internalization must be reported to FINRA's Trade Reporting Facility (TRF). These trades are classified in TAQ with exchange code "D." In addition, these trades are often given a small amount of price improvement that is typically a fraction of a cent. For all trades with the exchange code "D," Boehmer et al. (2021) tag those trades with prices that end with a fractional penny in the range of (0, 0.4) as sales and those trades with prices that end with a fractional penny in the range of (0.6, 1) as purchases.[8] We use the same rule to identify buys and sells. In our main analysis, we exclude retail trades greater than \$100,000 (as identified with the BJZZ algorithm) because our primary interest is in small retail investors and mean trade sizes at U.S. retail brokers tend to be much less than this threshold.[9] Some argue retail marketable orders perform better

[8]In a recent working article, Barber, Huang, Jorion, Odean, and Schwarz (2022) document the use of quote midpoints to sign trades is more accurate than the use of the subpenny digit. The main results of this analysis are similar if we use quote midpoints rather than the subpenny digit to sign trades.

[9]Gargano and Rossi (2018) report a mean trade size of \$16,000 at a U.S. brokerage firm. Barber and Odean (2000) report mean trade size for buys (sells) of \$13,707 (\$11,205). Trades above \$100,000 represent 1.7% of the number of trades and 31.4% of the value of trades identified using the BJZZ algorithm. In a Mar. 2, 2021, draft of this article we report all results including trades above \$100,000 and reach similar conclusions. In Section IV, we analyze results by trade size (including trades above \$100,000) and find smaller retail trades generate bigger losses. Note that this algorithm only identifies marketable orders because non-marketable limit orders are executed at whole pennies (Boehmer et al. (2021)); the algorithm only identifies retail trades that execute off-exchange (i.e., with exchange code "D") or retail trades executed at a whole penny or within the fractional penny range [0.4 to 0.6]; and, it will incorrectly sign buys in the fractional penny range (0, 0.4) and sells in the fractional penny range (0.6, 1). Finally, non-retail trades with exchange code "D" may be misidentified as retail. These issues are discussed in detail in Barber et al. (2022).

than retail limit orders (Linnainmaa (2010), Kelley and Tetlock (2013)). If so, our analysis will overstate the profitability of retail trades. Despite this shortcoming, BJJZ argue that the price improvement algorithm provides a more comprehensive view of retail trading than studies that rely on data from a single broker (e.g., Barber and Odean (2000), Barrot, Kaniel, and Sraer (2016)), a single wholesaler (Kelley and Tetlock (2013)), or retail trades executed on the NYSE (Kaniel, Liu, Saar, and Titman (2012)).

We limit the sample to U.S. common stocks (CRSP share code 10 or 11) traded on NYSE, AMEX, and NASDAQ during normal trading hours (9:30:00–16:00:00) from Jan. 2010 to Dec. 2019. We exclude stocks impacted by the Tick Size Pilot program between Oct. 2016 and Oct. 2018. On Oct. 3, 2016, following an order from SEC, the National Securities Exchanges and FINRA implemented a 2-year Tick Size Pilot program. The order approved the NMS Plan for a 2-year period and officially commenced. In two of the test groups (G2 and G3), which limit trading prices at \$0.05 increments, we observe a sizable drop in the trades identified as retail trades. Therefore, we drop stocks in the two groups during the Tick Size Pilot program.[10] Because the main part of our analysis involves the measurement of retail order imbalance, we limit our analysis to stocks in which there are at least 10 retail transactions in a trading day.

B. Measuring Order Imbalance

Consider a market participant who is trying to assess retail sentiment in stock i on day t. Stocks that are purchased more than average have positive retail sentiment, stocks purchased less, negative. However, for some stocks the participant observes many trades, for others, fewer. Whether the participant can conclude the retail sentiment is relatively bullish will thus be a function of both the proportion of trades that are buys and the number of trades observed in the stock (i.e., the reliability of the estimate).

To formalize this intuition, define b_{it} (s_{it}) as the number of retail buys (sells) for stock i, day t, and the total volume of retail trades as $v_{it} = b_{it} + s_{it}$. The buy proportion for stock i, day t is

(1) $$\mathrm{BP}_{it} = \frac{b_{it}}{b_{it} + s_{it}}.$$

The market-wide retail order imbalance is

(2) $$\mathrm{BP}_{mt} = \frac{\sum_i (b_{it})}{\sum_i (b_{it} + s_{it})}.$$

We lean on the properties of the binomial distribution and consider the benchmark case where the probability of observing a trade in stock i on day t is equal to the probability of observing a trade in the market that is a buy on day t ($\mathrm{BP}_{it} = \mathrm{BP}_{mt}$).

[10]Most of the pilots started around Oct. 2016 and ended around Oct. 2018. Stocks in the first test group and the control group did not experience a discernable change in trades identified as retail trades by the algorithm.

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Using the properties of the binomial distribution, we construct a standardized measure of order imbalance (SOI_{it}) as

$$\text{(3)} \qquad \mathrm{SOI}_{it} = \frac{\mathrm{BP}_{it} - \mathrm{BP}_{mt}}{\sigma(\mathrm{BP}_{it})},$$

where the denominator represents the standard deviation of the probability of observing a buy under the null hypothesis and decreases with trade size (v_{it}):

$$\text{(4)} \qquad \sigma(\mathrm{BP}_{it}) = \frac{1}{v_{it}} \sqrt{(v_{it})(\mathrm{BP}_{mt})(1 - \mathrm{BP}_{mt})}.$$

Thus, the market participant concludes retail sentiment for a stock is bullish if the buy proportion for the stock exceeds that of the market (the numerator), but the confidence in this conclusion is scaled by the standard deviation of the buy proportion under the assumption that retail trades are drawn from a binomial distribution with the probability of observing a buy equal to the market-buy proportion (BP_{mt}).

In Tables 1 and 2, we also report the buy–sell imbalance BSI_{it}, which is an unscaled linear transformation of the buy proportion in equation (1): $\mathrm{BSI}_{it} = 2(\mathrm{BP}_{it} - 0.50)$. We prefer the standardized measure of order imbalance to the unscaled version because the unscaled version tends to push stocks with fewer trades to the extreme order imbalance bins although order imbalance for these stocks is likely less informative regarding retail sentiment. Nonetheless, we report results based on an unscaled version of retail order imbalance in the Supplementary Material and reach similar conclusions.

C. Measuring Abnormal Volume

The second key measure in our analysis is SARV (SARV_{it}). On day t, we compare the observed number of retail trades (v_{it}) to the mean level of retail trade over trading days $t-45$ to $t-6$ scaled by the standard deviation of retail volume over the same period:

$$\text{(5)} \qquad \mathrm{SARV}_{it} = \frac{(v_{it} - \overline{v}_{it})}{\sigma(v_{it})},$$

where,

$$\text{(6)} \qquad \overline{v}_{it} = \sum_{\tau=t-45}^{t-6} \frac{v_{i\tau}}{T} \text{ and}$$

$$\text{(7)} \qquad \sigma^2(v_{it}) = \sum_{\tau=t-45}^{t-6} \frac{(v_{i\tau} - \overline{v}_{it})^2}{T-1}.$$

We calculate the pre-event volume mean, $\overline{v}_{it}$, and variance, $\sigma^2(v_{it})$, across T days, discarding days in the pre-event window with less than 10 trades (the same restriction we impose on the sample for inclusion in the event day t sample). We define ARV for stock i on day t as retail volume scaled by the pre-event volume mean:

TABLE 1

Summary Statistics on Retail Trades

In Table 1, statistics are calculated across stock-day observations for stock days with a minimum of 10 retail trades. #BUYS (#SELLS) counts each purchase (sale) as a single observation. $BOUGHT ($SOLD) counts each purchase (sale) as its dollar volume. #BSI ($BSI) is the buy–sell imbalance based on the number (value) of buys and sales or (buys − sells)/(buys + sells). Standardized order imbalance (SOI) is calculated as the percent of buys less the market-wide percent of buys for the day scaled by the standard deviation of percent buys (assuming a binomial distribution). Abnormal retail volume (ARV) is the ratio of number of retail trades on day t to the mean from $t-45$ to $t-6$. Standardized abnormal retail volume (SARV) is the number of retail trades standardized using the mean and standard deviation of retail trading in a 40-day window, $t-45$ to $t-6$.

	No. of Obs.	Mean	Std. Dev.	Min	25th Percentile	Median	75th Percentile	Max
#BUYS	6,851,685	158	533	0	16	43	125	87,472
#SELLS	6,851,685	153	467	0	17	45	126	61,211
SHARES_BOUGHT (000)	6,851,685	51	317	0	3	9	30	131,756
SHARES_SOLD (000)	6,851,685	51	328	0	3	10	31	217,103
$BOUGHT (000)	6,851,685	1,294	6,748	0	41	159	672	1,052,503
$SOLD (000)	6,851,685	1,278	6,384	0	44	167	686	980,427
#BSI = (B − S)/(B + S)	6,643,308	−0.018	0.292	−1.000	−0.182	−0.006	0.150	1.000
$BSI = ($B − $S)/($B + $S)	6,643,308	−0.023	0.325	−1.000	−0.206	−0.013	0.164	1.000
SOI	6,643,308	−0.244	3.551	−117.747	−1.882	−0.265	1.354	143.093
ARV	6,643,205	1.031	0.788	0.186	0.586	0.835	1.189	5.389
SARV	6,643,205	0.123	1.438	−1.513	−0.642	−0.270	0.358	8.065

(8) $$ARV_{it} = \frac{v_{it}}{\bar{v}_{it}}.$$

D. Summary Statistics

Table 1 presents summary statistics across stock-day observations. On average across these stock-day observations, there are 158 retail buys and 153 retail sells (a total of 311 retail trades). This corresponds to a mean (median) stock-day purchase of 51,000 (10,000) shares with a dollar value of $1,294,000 ($159,000). Statistics for retail sales across stock-day observations are similar. Retail volume is heavily skewed and concentrated in a few companies, similar to what we observe in the distribution of market volume and market capitalization.

Order imbalance (BSI), defined as the difference between buys and sells scaled by their sum, has a small but negative mean and median based on the number or value of trade. SOI also has a negative mean and median (−0.244 and −0.265). SOI is also positively skewed, which indicates retail buying is more likely to be concentrated than retail selling. This is noteworthy as it is consistent with models of attention-induced trading by retail investors, which posit that attention concentrates buying more than selling activity (Barber and Odean (2008), Barber, Huang, Odean, and Schwarz (2021)). Order imbalance based on number of retail trades (the focus of prior work) has a 75.1% correlation with order imbalance based on dollars traded and 74.9% correlation with SOI (our preferred measure of order imbalance). The two measures of abnormal retail volume (ARV and SARV) are also positively skewed and highly correlated (93.8%), which indicates that volume tends to concentrate on a few days for the same stock.[11]

[11]The slightly positive means of the abnormal volume measures results from the pre-event window that we employ. If we calculate retail volume using a window that spans the event day (e.g., −20 to +20)

TABLE 2

Order Imbalance, Firm Size, and Volume by Standardized Order Imbalance Quintiles

Table 2 shows quintile sorts, performed daily, based on standardized order imbalance (SOI). Statistics are calculated across 2,516 trading days. We require a minimum of 10 retail trades on each stock day. See Table 1 for detailed variable descriptions.

	SOI Quintile				
	Q1	Q2	Q3	Q4	Q5
Panel A. Mean Order Imbalance Measures					
SOI	−4.647	−1.563	−0.267	1.034	4.225
#BSI	−0.362	−0.198	−0.024	0.155	0.337
$BSI	−0.302	−0.174	−0.026	0.125	0.263
Panel B. Mean Market Cap and Volume Statistics					
MEAN_MARKET_CAP ($B)	10.53	5.44	5.06	5.39	10.86
%TOTAL_MARKET_CAP	28.5%	14.4%	13.4%	14.3%	29.3%
MEAN_TOTAL_VOLUME ($000)	80,163	39,901	37,122	40,227	91,483
%TOTAL_VOLUME	27.8%	13.8%	12.8%	14.0%	31.6%
MEAN_RETAIL_VOLUME ($000)	3,615	1,552	1,437	1,628	4,909
%TOTAL_RETAIL_VOLUME	27.3%	11.8%	11.0%	12.5%	37.4%
MEAN_RETAIL_BUYS ($000)	1,573	736	716	851	2,732
%TOTAL_RETAIL_BUYS	23.56%	11.15%	10.88%	12.98%	41.43%
MEAN_RETAIL_SALES ($000)	2,042	816	721	777	2,177
%TOTAL_RETAIL_SALES	31.1%	12.6%	11.1%	12.0%	33.3%
MEAN_ARV	1.15	0.91	0.89	0.94	1.27
MEAN_SARV	0.34	−0.09	−0.13	−0.05	0.52
#STOCKS	530.84	531.24	531.25	531.24	531.64
Stock-day obs.	1,327,640	1,328,641	1,328,645	1,328,641	1,329,638
Panel C. Mean Market Cap and Volume Statistics for the Top SARV Decile					
MEAN_MARKET_CAP ($B)	7.74	4.97	4.85	4.95	9.73
%TOTAL_MARKET_CAP	2.8%	0.9%	0.8%	1.0%	4.2%
MEAN_TOTAL_VOLUME ($000)	116,655	71,986	69,684	70,148	138,330
%TOTAL_VOLUME	5.3%	1.6%	1.5%	1.7%	7.5%
MEAN_RETAIL_VOLUME ($000)	6,287	3,486	3,363	3,471	8,580
%TOTAL_RETAIL_VOLUME	6.6%	1.7%	1.6%	1.9%	10.8%
MEAN_RETAIL_BUYS ($000)	2,749	1,685	1,683	1,793	4,783
%TOTAL_RETAIL_BUYS	5.2%	1.7%	1.6%	2.0%	12.9%
MEAN_RETAIL_SALES ($000)	3,538	1,800	1,680	1,678	3,797
%TOTAL_RETAIL_SALES	8.1%	1.9%	1.6%	1.9%	8.8%
MEAN_ARV	2.81	2.59	2.59	2.62	2.88
MEAN_SARV	3.53	3.21	3.21	3.22	3.58
#STOCKS	53.54	53.57	53.57	53.57	53.61
Stock-day obs.	133,897	133,985	133,981	133,985	134,074

Much of our analysis focuses on daily quintile sorts based on standardized retail order imbalance (SOI). In Panel A of Table 2, we present the mean order imbalance for each of the five quintiles on the sorting day by first calculating the mean order imbalance within each quintile on the sorting day and then averaging across the days in our sample. Stocks with the most extreme SOI also have the biggest buy–sell imbalances based on number or value of retail trades.

Panel B of Table 2 presents statistics on mean market cap and mean volume across stock-day observations for each SOI quintile. Panel C of Table 2 presents the same statistics for the top SARV deciles for each SOI quintile. In both Panels B and C, larger firms and firms with greater volume tend to end up in the extreme quintiles. This is partly because the larger volume of retail trades in these large, high-volume stocks allows for a more precise estimate of order imbalance.

the means are very close to 0. We choose to use a pre-event window to avoid any concerns that the calculation of the mean using a post-event window creates a look-ahead bias.

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In contrast, if we sort on order imbalance based on number of trades (#BSI), the extreme quintiles are populated by relatively small stocks (see Table A1 in the Supplementary Material), which represent a small percent of total market volume. We prefer the standardized measure because it accounts for both the level of order imbalance and the precision with which it is estimated. Our empirical results do not hinge on this choice, and we present key results for the unstandardized measure of order imbalance in the Supplementary Material. Firms in the top SARV deciles (Panel C) tend to be smaller than those in the bottom 9 SARV deciles but they have greater total market volume in dollars.

III. The Retail Performance Paradox

A. Order Imbalance Trading Strategies

To replicate the observation that retail order imbalance positively predicts short-term returns, we analyze a trading strategy that sorts stocks by SOI quintiles on each trading day (t) and invests an equal-weighted portfolio of stocks in each quintile. In our main analysis, we focus on calendar time portfolios with holding periods of 1, 5, and 10 days because the returns associated with the strategy are indistinguishable from 0 beyond a 10-day holding period.

Specifically, the equal-weighted portfolio invests \$1 (or \$1/P_{it} shares) in stock i at the close of trading on the day t; P_{it} is the closing price of stock i on day t. The day $t + 1$ portfolio return is calculated as

(9)
$$R_{p,t+1} = \sum_{i=1}^{N} w_{itq} R_{i,t+1},$$

(10)
$$w_{itq} = \frac{S_{itq} P_{it}}{\sum S_{itq} P_{it}},$$

where $R_{i,t+1}$ is the stock return, w_{itq} is the weight, and S_{itq} is the total number of shares held for stock i on day t in quintile q. At a 1-day holding period, the weights represent equal weights. At holding periods beyond a day, we may have multiple positions in the same stock with different holding periods if, for example, a stock is part of the high-order imbalance quintile for several days in a row. At a horizon of 5 days, the number of shares held at the close of day t is

(11)
$$S_{itq} = \sum_{h=-4}^{0} \frac{I_{i,t-h,q}}{P_{i,t-h}}.$$

The numerator is an indicator variable, $I_{i,t-h}$, that equals 1 if the stock is in quintile q on day $t - h$. We consider horizons of 1, 5, and 10 days.[12] On each

[12]We invest in \$1/P shares rather than \$1 so that the portfolio weights are those associated with a strategy that does not involve daily rebalancing implicit in an equal-weighted strategy. The implicit rebalancing in an equal-weighted strategy leads to positively biased returns in the presence of bid–ask spreads.

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calendar day, the portfolio consists of positions that were entered in the five prior trading days; thus, the daily abnormal return multiplied by five will approximate the 5-day drift one would observe in the average position.

The daily portfolio abnormal return is the intercept of the regression (FF6 alpha) of the portfolio excess return on the Fama–French 5-factors plus a momentum factor:

$$R_{pt} - R_{ft} = \alpha + \beta\left(R_{mt} - R_{ft}\right) + \sum_{k=1}^{K} c_k F_t^k + e_{pt}, \tag{12}$$

where R_{ft} is the daily risk-free return, R_{mt} is the return on the value-weighted market index, and F_t^k are the factor returns related to size, value, investment, profitability, and momentum (taken from Ken French's online data library).

Table 3 summarizes the daily FF6 alphas for equal-weighted quintile portfolios. Consistent with prior research, we see in last column of Panel A's first row that

TABLE 3

Performance of Standardized Retail Order Imbalance Quintile Portfolios (Equal-Weighted)

Table 3 presents the daily abnormal return for equal-weighted portfolios based on quintiles of standardized retail order imbalance on day *t*. Stocks are further partitioned into two standardized abnormal volume groups on day *t*, top decile (SARV D10) versus bottom 9 deciles (SARV D1–D9). Daily abnormal returns are calculated at various holding periods (1 day, Panel A; 5 day, Panel B; 10 day, Panel C). FF6 alpha is the intercept of the regression of the portfolio excess return (portfolio return less risk-free rate) on the Fama–French 5-factor model plus a momentum factor. *t*-statistics are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	SOI Quintile					
	Lo 1	2	3	4	Hi 5	Diff (5–1)
Panel A. FF6 Daily Alpha (bps) for t + 1						
ALL_STOCKS	−1.92**	−0.75*	0.65	3.27**	3.65**	5.57**
	(−4.09)	(−1.99)	(1.75)	(8.49)	(6.31)	(10.00)
SARV D1–D9	−2.51**	−1.53**	−0.06	2.34**	3.74**	6.25**
	(−5.31)	(−4.07)	(−0.15)	(6.14)	(6.92)	(11.63)
SARV D10	1.72	2.42	2.46*	5.46**	−5.78**	−7.50**
	(1.20)	(1.96)	(2.15)	(4.23)	(−2.62)	(−3.08)
DIFFERENCE (SARV D10 − SARV D1–D9)	4.23**	3.95**	2.52*	3.13*	−9.52**	−13.76**
	(2.96)	(3.17)	(2.17)	(2.39)	(−4.42)	(−5.58)
Panel B. FF6 Daily Alpha (bps) from t + 1 to t + 5						
ALL_STOCKS	−0.74	−0.06	0.46	1.45**	1.14*	1.88**
	(−1.80)	(−0.21)	(1.62)	(4.73)	(2.40)	(5.96)
SARV D1–D9	−1.25**	−0.56	0.03	0.95**	1.27**	2.52**
	(−3.03)	(−1.89)	(0.10)	(3.10)	(2.77)	(8.16)
SARV D10	2.17**	1.38*	0.83	1.91**	−3.75**	−5.92**
	(2.66)	(2.26)	(1.41)	(2.90)	(−3.04)	(−5.14)
DIFFERENCE (SARV D10 − SARV D1–D9)	3.42**	1.94**	0.80	0.96	−5.02**	−8.44**
	(4.73)	(3.36)	(1.42)	(1.55)	(−4.46)	(−7.37)
Panel C. FF6 Daily Alpha (bps) from t + 1 to t + 10						
ALL_STOCKS	−0.66	0.03	0.32	1.09**	0.65	1.31**
	(−1.67)	(0.10)	(1.19)	(3.70)	(1.43)	(5.15)
SARV D1–D9	−1.08**	−0.44	−0.03	0.72*	0.66	1.74**
	(−2.70)	(−1.52)	(−0.10)	(2.45)	(1.49)	(6.84)
SARV D10	1.42*	1.32**	0.76	1.06*	−2.23*	−3.64**
	(2.23)	(2.80)	(1.59)	(2.02)	(−2.32)	(−4.45)
DIFFERENCE (SARV D10 − SARV D1–D9)	2.50**	1.76**	0.79	0.34	−2.89**	−5.38**
	(4.79)	(4.19)	(1.85)	(0.73)	(−3.52)	(−6.61)

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the 1-day abnormal return on the long–short portfolio for all stocks is 5.57 bps (t = 10.00). At a 5-day horizon (row 1 of Panel B), the abnormal daily return on the long–short portfolio is 1.88 bps (t = 5.96) (or a total of 9.40 bps across the 5-day holding period). And at a 10-day horizon (row 1 of Panel C), it is 1.33 bps (t = 5.15) (a total of 13.30 bps across the 10-day holding period).

Next, we examine order imbalance strategies by partitioning the sample into low and high retail volumes. Following results for "All Stocks" in each panel of Table 3, we present returns separately for the bottom 9 SARV deciles and the top SARV decile (rows labeled "SARV D1–D9" and "SARV D10"). (SARV deciles are calculated independently of order imbalance.) In Panel A, we see that the returns on the day following trade (t + 1) have different patterns conditional on the level of retail volume. The return spread across the extreme order imbalance quintiles (SOI Q5 and Q1) in the bottom 9 retail volume deciles (SARV D1–D9) is 6.25 bps (t = 11.63); in contrast, the return spread is −7.50 bps (t = −3.08) for the top retail volume decile (SARV D10). In other words, an equal-weighted long–short strategy based on retail order imbalance makes money for stocks traded less and losses money for the stocks traded most. The 13.78 bps difference between these two return spreads is statistically significant (t = −5.58). At horizons of 5 and 10 days (Panels B and C), the return spreads grow larger: 42.2 bps at 5 days (8.44 bps/day×5 days) and 53.8 bps at 10 days (5.38 bps/day×10 days). Note that these patterns are very similar to those depicted in Figure 1, which plots the event-time market-adjusted returns for the 5 days following the date of trade for the SOI long–short strategies that condition on abnormal trading volume.[13]

Both Table 3 and Figure 1 show that the future performance of stocks depends not only on retail order imbalance but on how heavily a stock was traded. Heavily traded stocks perform much worse the days after being traded. Note that the equal-weighted portfolio returns presented in Table 3 understate the relationship between retail trading volume and future returns. This is because stocks most heavily purchased within each partition of ARV underperform other stocks in that partition.

In Table 4, we present results analogous to those in Table 3 but weight each stock by the dollar value of purchases rather than equally. When we do so, performance in the top order imbalance quintile falls. For all stocks at a 1-day horizon, the performance drops from 3.65 bps when equal-weighted (Panel A of Table 3) to −4.47 bps when weighted by purchases (Panel A of Table 4). Within this top quintile, the difference is more dramatic for the top decile of ARV, which earns returns of −5.78 bps when equal-weighted and −20.36 bps when purchase weighted. In contrast to the equal-weighted portfolio returns of Table 3, the

[13]Table A2 in the Supplementary Material presents results based on quintile sorts of retail order imbalance without scaling by the standard deviation of retail order imbalance. Stocks with lower average daily retail trades tend to have more extreme retail order imbalances, in part, because of their small retail trade sample size. Therefore, smaller and low volume stocks are pushed to the extreme quintiles in Table A2 in the Supplementary Material although their extreme order imbalance may be due to small sample noise rather than attention-based trading. As a result, the interaction between high retail volume and order imbalance is most dramatic in the second from the top order imbalance quintile which, in this table, is populated by larger, higher volume stocks relative to those in the top order imbalance quintile.

TABLE 4

Performance of Standardized Retail Order Imbalance Quintile Portfolios (Purchase-Weighted)

Table 4 presents the daily abnormal return for purchase-weighted portfolios based on quintiles of standardized retail order imbalance on day *t*. Stocks are further partitioned into two standardized abnormal volume groups on day *t*, top decile (SARV D10) versus bottom 9 deciles (SARV D1–D9). Daily abnormal returns are calculated at various holding periods (1 day, Panel A; 5 day, Panel B; 10 day, Panel C). FF6 alpha is the intercept of the regression of the portfolio excess return (portfolio return less risk-free rate) on the Fama–French 5-factor model plus a momentum factor. *t*-statistics are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	SOI Quintile					
	Lo 1	2	3	4	Hi 5	Diff (5–1)
Panel A. FF6 Daily Alpha (bps) for t + 1						
ALL_STOCKS	−1.44 (−1.44)	−1.32 (−1.19)	−1.31 (−1.49)	0.45 (0.43)	−4.47** (−3.02)	−3.03 (−1.73)
SARV D1–D9	−1.35 (−1.67)	−1.08 (−1.41)	−0.94 (−1.24)	0.56 (0.72)	−0.10 (−0.10)	1.25 (1.04)
SARV D10	−3.47 (−1.08)	−2.04 (−0.63)	−3.74 (−1.50)	−3.29 (−0.99)	−20.36** (−3.56)	−16.90** (−2.63)
DIFFERENCE (SARV D10 − SARV D1–D9)	−2.12 (−0.65)	−0.96 (−0.29)	−2.80 (−1.09)	−3.85 (−1.14)	−20.26** (−3.52)	−18.14** (−2.80)
Panel B. FF6 Daily Alpha (bps) from t + 1 to t + 5						
ALL_STOCKS	−0.34 (−0.54)	−0.33 (−0.51)	−1.32* (−2.30)	−0.44 (−0.72)	−3.03** (−3.29)	−2.68** (−2.90)
SARV D1–D9	−0.13 (−0.23)	−0.22 (−0.43)	−1.37** (−2.62)	−0.24 (−0.46)	−0.92 (−1.20)	−0.78 (−1.00)
SARV D10	−0.26 (−0.15)	0.18 (0.09)	−1.02 (−0.70)	−1.58 (−0.89)	−10.77** (−4.03)	−10.51** (−3.94)
DIFFERENCE (SARV D10 − SARV D1–D9)	−0.12 (−0.07)	0.39 (0.21)	0.34 (0.24)	−1.34 (−0.75)	−9.85** (−3.74)	−9.73** (−3.65)
Panel C. FF6 Daily Alpha (bps) from t + 1 to t + 10						
ALL_STOCKS	−0.13 (−0.22)	−0.53 (−1.00)	−0.89 (−1.61)	−1.04 (−1.95)	−2.32** (−2.95)	−2.19** (−3.00)
SARV D1–D9	−0.16 (−0.30)	−0.44 (−0.96)	−0.83 (−1.77)	−0.83 (−1.78)	−0.94 (−1.30)	−0.78 (−1.15)
SARV D10	0.09 (0.07)	−0.27 (−0.21)	−0.98 (−0.72)	−1.71 (−1.24)	−7.14** (−3.90)	−7.23** (−4.03)
DIFFERENCE (SARV D10 − SARV D1–D9)	0.25 (0.20)	0.17 (0.13)	−0.15 (−0.11)	−0.88 (−0.66)	−6.20** (−3.58)	−6.45** (−3.64)

purchase-weighted returns of all portfolios in Table 4 are either statistically indistinguishable from 0 or reliably negative.

These results reveal a striking difference in the returns of order imbalance strategies that weight stocks equally versus strategies that weight stocks based on the intensity of retail trading. Consider three different weighting schemes with stocks weighted equally, by the value of trade, or by the number of trades. The equal-weighted strategy invests equal dollar amounts in each stock on the long (or short) side of the strategy. The second strategy weights by the value of trade, buying stocks in the top SOI quintile in proportion to dollars bought and shorting stocks in the bottom SOI quintile in proportion to dollars sold. The third strategy weights by the number of trades, buying stocks in the top SOI quintile in proportion to the number of buys and shorting stocks in the bottom SOI quintile in proportion to the number of sells. Crucially, the three strategies invest in exactly the same set of stocks and short exactly the same set of stocks; only the weighting schemes differ.

FIGURE 3

Returns to Long–Short Retail Order Imbalance Strategies: Equal Versus Trade Weighting

Figure 3 depicts the returns to a strategy that purchases stocks in the top standardized retail order imbalance (SOI) quintile and shorts stocks in the bottom SOI quintile. The equal-weighted strategy invests equal dollar amounts in each stock on the long (or short) side of the strategy. The strategy weighted by the value of trade buys stocks in the top SOI quintile in proportion to dollars bought and shorts stocks in the bottom SOI quintile in proportion to dollars sold. The strategy weighted by the number of trades buys stocks in the top SOI quintile in proportion to the number of buys and shorts stocks in the bottom SOI quintile in proportion to the number of sells. All strategies begin at the close on the day SOI order imbalance is measured (event day 0), buy the same stocks, and short the same stocks. Dashed lines represent 95% confidence intervals.

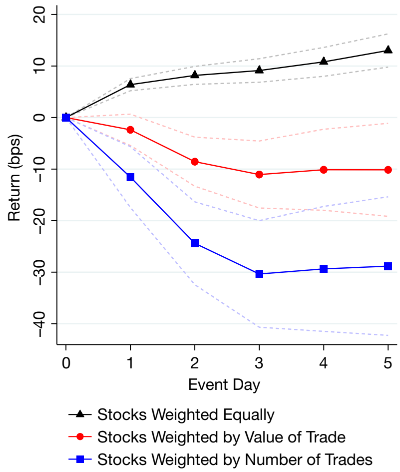

Figure 3 traces out the event-time market-adjusted returns to these three strategies. The equal-weighted long–short portfolio earns an abnormal return of 13.0 bps after 1 week (an annualized return of 6.6%). In contrast, the strategy that weights by the value of trade earns an abnormal return of −10.1 bps after 1 week (an annualized return of −5.1%). The long–short portfolio weighted by the number of trades earns an abnormal return of −28.8 bps after 1 week (an annualized return of −14.5%).

Just as more heavily purchased stocks perform worst on the days after trade, they also perform worst on the day that they are purchased. Referring to Graph A of Figure 2, we see that effective spreads vary little across SOI quintiles, though they are a bit lower in the extremes (likely because big stocks tend to end up in the extreme quintiles due to the standardization). Intraday price movement generally helps offset some of the spread costs, but the effect varies by SOI quintile and is smallest in the top SOI quintile (where most buying activity occurs). However, in Graph B of Figure 2, we observe very different patterns for stocks with heavy ARV (top decile of SARV). For the top SOI quintile (stocks heavily bought), the intraday price movement contributes far more to the losses of retail investors than does the effective spread. This echoes the pattern of poor returns for these stocks on the day after trade (Panel A of Table 3, row labeled SARV D10).

This interaction between the level of retail volume and the predictability associated with retail order imbalance is an important reason why retail investors lose from trading despite the fact the retail order imbalance positively predicts returns.

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B. Performance of Retail Investors

As described previously, we assess the predictive power of retail trades by comparing the return of an equal-weighted portfolio of stocks in the highest order imbalance quintile to the return of a portfolio of stocks in the lowest order imbalance portfolio. To analyze the actual performance of retail investors, we calculate the difference between the return of a retail purchase-weighted portfolio and the return of a retail sales-weighted portfolio. Weighting portfolios by how much retail investors bought or sold each stock closely tracks the actual retail profits and losses from trading. It also allows a direct comparison to the returns of the trading strategies based on quintiles of retail order imbalance. When the dollar value of sales and purchases are equal, which is approximately true during our sample period (see Table 1), the sign of the dollar-weighted return difference in any period will have the same sign of the actual retail profits or losses from trading. The magnitude of the gains or losses will depend on the intensity of trading, measured by portfolio turnover.

To see this, consider the following example: An investor holds a \$100,000 equity portfolio. Absent trading, the portfolio will earn 10% in the coming year. However, at the beginning of the year, the investor decides to sell \$50,000 in stock S to buy stock B. The \$50,000 purchase of stock B earns 10% during the year. The stock sold, stock S, earns 0% during the year, which implies the \$50,000 of stock that was originally held in the portfolio earned 20% (since the buy-and-hold option earned 10% = 50% × 0% + 50% × 20%). Thus, the return on the portfolio that traded is 15%, or a return improvement of 5 percentage points relative to the buy-and-hold counterfactual. Note that the return improvement of 5 percentage points is the turnover rate times the difference in the returns of stocks bought less stocks sold: 50%*(10%–0%) = 5%.

When sales and purchase activity are equal, we can summarize the relation between the return on a portfolio with trading (R_{pt}^{T}) and a counterfactual buy-and-hold portfolio (R_{pt}):

$$R_{pt}^{T} - R_{pt} = \mathrm{TO}_t \left(R_{pt}^{b} - R_{pt}^{s} \right), \tag{13}$$

where TO_{it} is the turnover in the stock portfolio, defined as half the dollar value of purchases plus sales divided by the portfolio size, R_{pt}^{b} is the purchase-weighted return on stocks bought, and R_{pt}^{s} is the sales-weighted return on stocks sold. (See the Appendix for a detailed derivation of the equation.) The key takeaway is that the sign of the investor profits is the same sign as the difference in return between stocks bought and stocks sold; the magnitude of the profits (or losses) will be determined by the amount of turnover in the portfolio.[14]

We construct a buy portfolio assuming shares of each stock are purchased at the observed purchase price of retail investors. Of course, different investors buy

[14]This analysis assumes the portfolio is self-funded and thus trading profits are confined to an investor's security selection ability. If aggregate sales and purchases differ, investors might gain from market timing. To investigate this possibility, we regress daily market returns on five daily lagged values of marketwide retail order imbalance. The coefficients are all statistically insignificant with t-statistics ranging from −1.28 to 0.99.

TABLE 5

Trade-Weighted Returns on Stocks Bought Versus Stocks Sold on Day of Trade Versus Subsequent Days

Table 5 presents intraday return on the day of trade (Panel A) and the subsequent daily abnormal return (Panels B–E) for portfolios based on day *t* trades of retail investors. Columns 1–3 weight investments in proportion to the dollar value of trades; columns 4–6 weight investment in proportion to the number of trades. In Panel A, the trade day return is calculated using the trade price and closing price on the same day. Abnormal returns after the trading day are based returns earned from the close of trading on the date of trade at various holding period (1 day, Panel B; 5 day, Panel C; 10 day, Panel D; days 11–21, Panel E). Market-adjusted returns are portfolio returns minus the value-weighted market return. FF6 alpha is the intercept of the regression of the portfolio excess return (portfolio return less risk-free rate) on the Fama–French 5-factor model plus a momentum factor. *t*-statistics are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Weighted by Dollar Value of Trades (average dollar invested)			Weighted by No. of Trades (average trade)		
	Buys	Sells	Buys–Sells	Buys	Sells	Buys–Sells
	1	2	3	4	5	6
Panel A. Intraday Return on Trading Day (t)						
RAW_RETURN (bps)	−1.92	0.68	−2.60**	−9.67**	−3.48**	−6.19**
	(−1.84)	(0.66)	(−40.97)	(−8.22)	(−3.10)	(−41.42)
Panel B. Daily Alpha on t + 1						
MKT_ADJ_RET (bps)	−2.15*	−2.38**	0.24	−7.81**	−7.37**	−0.44*
	(−2.52)	(−2.97)	(1.91)	(−8.82)	(−8.77)	(−2.44)
FF6_ALPHA (bps)	−2.35**	−2.57**	0.23	−7.64**	−7.19**	−0.46*
	(−3.25)	(−3.82)	(1.85)	(−11.20)	(−11.66)	(−2.53)
Panel C. Daily Alpha from t + 1 to t + 5						
MKT_ADJ_RET (bps)	−1.27	−1.28	0.01	−4.98**	−4.61**	−0.37**
	(−1.78)	(−1.86)	(0.10)	(−6.22)	(−5.93)	(−3.59)
FF6_ALPHA (bps)	−1.54**	−1.53**	−0.01	−4.89**	−4.51**	−0.39**
	(−2.75)	(−2.87)	(−0.22)	(−8.89)	(−8.78)	(−3.81)
Panel D. Daily Alpha from t + 1 to t + 10						
MKT_ADJ_RET (bps)	−0.95	−0.90	−0.05	−4.11**	−3.80**	−0.31**
	(−1.38)	(−1.35)	(−0.92)	(−5.24)	(−4.96)	(−3.76)
FF6_ALPHA (bps)	−1.24*	−1.17*	−0.07	−4.05**	−3.72**	−0.33**
	(−2.37)	(−2.33)	(−1.36)	(−7.87)	(−7.69)	(−4.00)
Panel E. Daily Alpha from t + 11 to t + 21						
MKT_ADJ_RET (bps)	−0.58	−0.56	−0.02	−3.04**	−2.91**	−0.13
	(−0.86)	(−0.86)	(−0.33)	(−3.88)	(−3.80)	(−1.78)
FF6_ALPHA (bps)	−0.91	−0.87	−0.04	−3.02**	−2.86**	−0.16*
	(−1.85)	(−1.83)	(−0.91)	(−6.23)	(−6.25)	(−2.15)

at different prices on the same day, so we weight the intraday returns across trades by the value of trade. Thus, the portfolio includes the intraday return on the day of trade, which is generally ignored by the order imbalance strategy of the prior section but is obviously a return experienced by retail investors. Similar to the order imbalance strategy, we trace out the returns on the buy portfolio 1, 5, and 10 days after trade. There is an analogous calculation for the sell portfolio.

In Table 5, we present the returns of trading strategies that mimic the buys or sells of retail investors and assume execution at observed trading prices on the day of trade. The first three columns weight each stock by the dollar value of trades (buys or sells) and represent the return on the average dollar invested by retail investors. The second three columns weight each stock by the number trades and represent the return on the average trade by a retail investor. (In this analysis, it does not make sense to weight by stocks because retail investors tend to buy and sell the

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same stocks but do so with differing intensities.) The difference in returns to the buy and sell strategies provides an assessment of whether investors gain or lose from trading on the average dollar invested (column 3) or the average trade (column 6).

Retail investors consistently lose from trading. For the average dollar invested (average trade) on the day of trade, buys lose 1.92 bps (−9.67 bps) and sells gain 0.68 bps (−3.48 bps). The difference in the trade-day returns of buys and sells of −2.60 bps (−6.19 bps) is statistically significant.[15] Following the day of trade, both buys and sells earn poor abnormal returns.

The negative performance in the days following sells raises the question of whether investors are profiting from good timing in their selling decisions. On average, they are not. Consider two conditions: 1) stock/days in which retail investors buy more than they are sell, and 2) stock/days in which they sell more than they buy.

First, consider condition 1, stocks/days in which retail investors are net buyers. In Panel B of Table 2, we see that slightly more selling takes place in order imbalance quintiles 4 and 5 (12.0% + 33.3% = 45.3%) than in order imbalance quintiles 1 and 2 (31.1% + 12.6% = 43.7%). Retail investors do sell a lot of stock in quintiles 4 and 5, but they buy even more. Though sells in these quintiles may appear to be correctly predicting returns, retail investors as a group are losing money on these stocks because they are net buyers.

Now consider condition 2, stock/days in which retail investors are net sellers. Table A3 in the Supplementary Material presents the results analogous to columns 1–3 of Table 5. The difference is that instead of including all stocks bought in the "buys" column and all stocks sold in the "sells" column, we only include stocks in the "buys" column if retail investors were net buyers of the stock that day and only include them in the "sells" column if retail investors were net sellers the stock that day. We weight each stock by its net dollar value of buys (if in the buy column) and net dollar value of sells (if in the sells column). On the day of trade, stocks that are net sold have a closing price that is 4.13 bps above the selling price. Thus, on average, on the day of trade investors are selling into rising prices. The next day these stocks drop, on average, 2.47 bps. This is the right direction for the previous day's sellers, but not enough to make up for the same-day loss. The next day reversal is consistent with the existing literature on short-term reversals.

Thus, in condition 1, the selling behavior of retail investors appears to predict returns but retail investors are actually net buyers. In condition 2, retail investors are net sellers but lose more on the day of trade than they recapture.

In our empirical analysis, we calculate the mean daily abnormal return on a buy portfolio that mimics the buying of retail investors less the mean daily abnormal return on a portfolio that mimics the selling of retail investors, both weighted by the value of trade in our primary analysis. There are two reasons that the return difference on these dollar-weighted portfolios might depart from the actual retail dollar profits. First, as discussed previously, the calculation assumes that dollars bought equal dollars sold, which is approximately true on average (see Table 1). However, if purchases perform better (worse) on days when

[15]We present raw, rather than abnormal returns, because the returns on the day of trade represent returns for less than full day. Market-adjusted returns necessarily yield the same return spread of −2.60 bps. FF6 alphas yield a return spread of −2.64.

purchases are greater than sales then the mean return difference will underestimate (overestimate) retail performance. Second, the calculation of the mean daily abnormal return weights each day equally. If retail investors perform better (worse) on days with high levels of retail trading (or turnover), we would underestimate (overestimate) the performance of retail investors because of the positive relation between turnover and performance.

We address these two concerns by calculating dollar profits (rather than returns) as in Barber, Lee, Liu, and Odean (2009). The raw dollar profits (\$RAW) from trading are calculated as the difference to the dollar profits from purchases and sales:

$$\text{(14)} \qquad \$\mathrm{RAW} = V_{b,t-1}R_{bt} - V_{s,t-1}R_{st},$$

where $V_{b,t-1}$ ($V_{s,t-1}$) is the value of the buy portfolio at the close of day $t-1$ and R_{bt} (R_{st}) is the day t return on the buy (sell) portfolio. The market-adjusted dollar profits from trading are calculated as

$$\text{(15)} \qquad \$\mathrm{MA} = V_{b,t-1}(R_{bt} - R_{mt}) - V_{s,t-1}(R_{st} - R_{mt}) = \$\mathrm{RAW} - (V_{b,t-1} - V_{s,t-1})R_{mt},$$

where R_{mt} is the value-weighted market return on day t. Note that market-adjusted profit equals the raw profits minus a term that reflects the relative size of the buy and sell portfolio and the market return. If the buy portfolio is larger than the sell portfolio on a day when the market goes up, market-adjusted profits for the buy minus sell portfolio will be less than raw profits (and vice versa).

In Table 6, we summarize the dollar profits earned on stocks bought and sold. Consistent with the return analysis of Table 5, the losses on the day of trade are statistically significant. In contrast to the return analysis, we find the market-adjusted dollar losses on stocks bought minus those sold are statistically significant at horizons of 5 and 10 days (Panels C and D).[16]

C. The Concentration of Retail Buys and Sells

Barber and Odean (2008) argue that retail buying will be concentrated in stocks that capture the attention of retail investors because they can buy anything that captures attention but tend to sell only what they own. In this section, we report the concentration of purchases and sales across 5 SOI quintiles by 10 SARV deciles. The top order imbalance quintile represents 42.6% of total retail purchases and the top decile of ARV within this quintile represents 12.9% of all retail purchases (by dollars traded). Consistent with the theories of attention-based trading, it is these stocks with heavy retail buying that earn the worst returns on the day of trade and the days that follow.

In Table 7, we present three heat maps based alternatively on buys, sells, or the difference between buys and sells. Darker colors represent greater density.

[16]Our main analysis focuses on retail trades with a value less than \$100,000 because we are most interested in the performance of small retail investors. Including the relatively rare retail trades placed for over \$100,000 does not materially affect the average performance (see Tables A4 and A5 in the Supplementary Material for returns and dollar profits, respectively). Section III of this article discusses and analyzes the relation between trade size (including those trades above \$100,000) and performance.

TABLE 6

Trade-Weighted Dollar Profits on Stocks Bought Versus Stocks Sold on Day of Trade Versus Subsequent Days

Table 6 presents intraday raw dollar profits on the day of trade (Panel A) and the subsequent the daily raw dollar profits and market adjusted dollar profits (Panels B–E) for trade-weighted portfolios (by dollars traded) based on day *t* trades of retail investors. In Panel A, the trade day dollar profits are calculated using the trade price and closing price on the same day. Abnormal dollar profits after the trading day are based on returns earned from the close of trading on the date of trade at various holding period (1 day, Panel B; 5 day, Panel C; 10 day, Panel D, days 11–21, Panel E). *t*-statistics are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Buys	Sells	Buys–Sells
Panel A. Intraday Raw Dollar Profits on Trading Day (t)			
RAW_PROFIT ($000)	−841.03*	32.28	−873.31**
	(−2.00)	(0.08)	(−23.71)
Panel B. Dollar Profits for t + 1			
RAW_PROFIT ($000)	800.89	742.06	58.83
	(0.90)	(0.86)	(0.75)
MKT_ADJ_PROFIT ($000)	−796.40*	−790.63**	−5.77
	(−2.44)	(−2.59)	(−0.12)
Panel C. Dollar Profits from t + 1 to t + 5			
RAW_PROFIT ($000)	6,697.51	6,809.21	−111.70
	(1.56)	(1.62)	(−0.49)
MKT_ADJ_PROFIT ($000)	−2,388.41	−2,123.30	−265.10*
	(−1.76)	(−1.64)	(−2.02)
Panel D. Dollar Profits from t + 1 to t + 10			
RAW_PROFIT ($000)	14,144.5	14,267.69	−123.19
	(1.67)	(1.72)	(−0.32)
MKT_ADJ_PROFIT ($000)	−3,711.24	−3,214.88	−496.37*
	(−1.42)	(−1.29)	(−2.27)
Panel E. Dollar Profits from t + 11 to t + 21			
RAW_PROFIT ($000)	8,435.45*	8,528.08**	−92.63
	(1.96)	(2.02)	(−0.51)
MKT_ADJ_PROFIT ($000)	−1,076.59	−953.23	−123.36
	(−0.82)	(−0.76)	(−1.21)

In Panel A, we report the percent of all purchases in each of the 50 cells created by SOI quintile sorts and SARV decile sorts. On each day, stocks are partitioned into 50 bins based on quintiles of SOI and deciles of SARV. SARV deciles are constructed within each quintile. For each partition, we calculate the percent of buys (or sells) by value that falls into each cell on day *t*. For each cell, we then calculate the mean percent of retail buys (or sells) across days.

In Panel A of Table 7, 12.9% of all retail purchases occur in the top order imbalance quintile and the top decile of ARV (by dollars traded). Summing all rows within the top order imbalance quintile reveals 42.6% of all retail purchases occur in the top order imbalance quintile. However, the effect of a stock's return on retail performance does not simply depend upon how much of this stock retail investors buy, but on how much more they buy than they sell. If the dollar value of purchases equals the dollar value of sales in a cell, then trades in that cell will have little influence on performance. However, if the value of purchases greatly exceeds the value of sales (or vice versa), returns for that cell will contribute substantially to performance.

In Panel C of Table 7, we report the difference between the mean daily percent of retail buys (Panel A) and retail sells (Panel B) for each of the 50 cells. Darker blue (red) cells represent more intense buying (selling). Column Q3 reports the difference in buying versus selling behavior for the middle SOI quintile. As one would expect, for this order imbalance quintile, the differences in buying and selling are effectively 0 and thus the influence of this quintile on retail performance is effectively 0. Buying exceeds selling in the top two SOI quintiles (Q4 and Q5). However, in Q4, differences in buying and selling are small. This is also true for the low SARV cells of Q5. In fact, for Q4 and Q5

TABLE 7

Percent of Retail Buys, Retail Sells, and Their Difference by Abnormal Retail Volume and Order Imbalance

Table 7 presents the percent of all trades that fall into 50 mutually exclusive categories formed on the basis of abnormal retail volume (ARV) and retail order imbalance. Standardized abnormal retail volume (SARV) deciles are constructed within each quintile. For each partition, we calculate the percent of buys (or sells) by value that fall into each cell on day *t*. For each cell, we then calculate the mean percent of retail buys (or sells) across days. The numbers in Panel A represent the mean daily percent of retail buys in each of the 50 partitions; the color scale goes from darkest (maximum) to lightest (minimum). The numbers in Panel B are the same statistic for retail sells; the color scale goes from darkest (maximum) to lightest (minimum). The numbers in Panel C represent the difference between the mean daily percent of retail buys less the mean daily percent of retail sells in each of the 50 partitions; the darkest shades are in the cell in which buys most exceed sells (sells most exceed buys).

		Standardized Retail Order Imbalance Quintiles (*SOI*)				
		Sell Q1	Q2	Q3	Q4	Buy Q5
Panel A. Mean Daily Percent of Retail Buys						
Deciles of Standardized Abnormal Retail Volume (SARV)	Lo SARV (D1)	1.71%	0.97%	0.95%	1.04%	1.70%
	D2	1.64%	0.88%	0.87%	0.97%	1.82%
	D3	1.66%	0.91%	0.89%	0.97%	2.05%
	D4	1.64%	0.94%	0.92%	1.08%	2.33%
	D5	1.75%	0.97%	0.94%	1.10%	2.66%
	D6	1.93%	1.01%	1.02%	1.21%	3.19%
	D7	2.24%	1.12%	1.09%	1.36%	4.09%
	D8	2.46%	1.17%	1.15%	1.44%	5.25%
	D9	2.88%	1.22%	1.23%	1.55%	6.58%
	Hi SARV (D10)	5.24%	1.67%	1.57%	2.02%	12.93%
Panel B. Mean Daily Percent of Retail Sells						
Deciles of Standardized Abnormal Retail Volume (SARV)	Lo SARV (D1)	2.27%	1.13%	0.98%	0.95%	1.40%
	D2	2.14%	1.03%	0.88%	0.90%	1.52%
	D3	2.18%	1.06%	0.93%	0.90%	1.69%
	D4	2.17%	1.09%	0.95%	1.00%	1.92%
	D5	2.34%	1.12%	0.97%	1.02%	2.17%
	D6	2.58%	1.16%	1.05%	1.12%	2.57%
	D7	3.00%	1.28%	1.13%	1.27%	3.29%
	D8	3.32%	1.33%	1.19%	1.34%	4.22%
	D9	3.88%	1.38%	1.26%	1.45%	5.23%
	Hi SARV (D10)	8.11%	1.88%	1.60%	1.86%	8.81%
Panel C. Mean Daily Percent of Retail Buys Less Mean Daily Percent of Retail Sells						
Deciles of Standardized Abnormal Retail Volume (SARV)	Lo SARV (D1)	−0.57%	−0.16%	−0.03%	0.08%	0.30%
	D2	−0.49%	−0.15%	−0.01%	0.08%	0.31%
	D3	−0.52%	−0.15%	−0.03%	0.08%	0.35%
	D4	−0.53%	−0.15%	−0.03%	0.08%	0.42%
	D5	−0.59%	−0.15%	−0.03%	0.08%	0.49%
	D6	−0.65%	−0.15%	−0.03%	0.09%	0.62%
	D7	−0.76%	−0.16%	−0.03%	0.10%	0.80%
	D8	−0.86%	−0.16%	−0.03%	0.10%	1.03%
	D9	−1.00%	−0.16%	−0.03%	0.10%	1.35%
	Hi SARV (D10)	−2.87%	−0.21%	−0.03%	0.16%	4.12%

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combined, the summed value of purchases as a percent of all purchases exceeds the summed value of sales as a percent of all sales by 10.74% of which 4.12% is in the top SARV decile of Q5 alone. Returns of stocks in this one cell (the stocks with the worst returns both on the day of trade and the days that follow) will have nearly as much influence on dollar-weighted retail performance as the returns for all other stocks in positive SOI cells combined.

D. Panel Regressions with Alternative Proxies for Attention

We argue that attention-driven trading explains why the underperformance of retail trades is concentrated in stocks with purchase volume. We further investigate the interaction of order imbalance and attention proxies in a regression setting using three proxies for attention proposed by Barber and Odean (2008): abnormal volume, extreme returns, and news.

Our first attention proxy is based on standardized abnormal volume (SAV_{it}) for stock i on day t, which we calculate identically to SARV but instead of the daily number of retail trades we use total daily dollar volume. Barber and Odean (2008) argue that stocks with high levels of market volume are likely to be attention-grabbing stocks. We estimate a panel regression of the following form:

$$r_{i,t+h} = a + \sum_{q|(q\neq 3)} b_q \text{SOI}_{it}^q + \sum_q c_q \text{SOI}_{it}^q * \text{HISAV}_{it} + \mu_{t+h} + e_{i,t+h}, \tag{16}$$

where $r_{i,t+h}$ is the daily return on stock i on day $t+h$, SOI_{it}^q is an indicator that takes a value of 1 if the stock is in SOI quintile $q = 1, 2, 3, 4, 5$ on day t, HISAV_{it} is an indicator that takes a value of 1 if the stock is in the top SARV decile day t, and μ_{t+h} are day fixed effects. Since we omit the middle order imbalance quintile, the b coefficients represent return differences relative to SOI quintile three. The c coefficients represent the incremental return on a stock that is in the top decile of retail order imbalance within each order imbalance quintile. Standard errors are clustered by day to address the cross-correlation of returns observed on the same day.

We summarize the results in Panel A of Table 8. The indicator variables on the order imbalance quintiles yield impressive return spread on the day following the measurement of order imbalance. On day $t+1$, stocks in the top order imbalance quintile ($q = 5$) earn an extra 3.78 bps ($t = 6.78$) relative to the baseline quintile (quintile 3) and stocks in the bottom quintile ($q = 1$) earn −2.18 bps ($t = -4.31$), a spread of 6.0 bps. Note that this analysis sorts stocks on daily order imbalance, weights stock-day observations equally, and does not include intraday returns on day t. In these respects, the analysis is similar to that reported for equal-weighted portfolios in Table 3. Indeed, the spread of 6.0 bps between the coefficients on the high and low SOI quintile indicators in column 1 (3.78 and −2.18, respectively) is close to the 6.3 bps performance spread between the high and low SOI quintile portfolios for stocks in the bottom 9 ARV deciles (Panel A of Table 3).

However, the interaction of order imbalance and heavy trading volume generates a markedly different pattern. On day $t+1$, stocks in the top order imbalance quintile and the top decile of SAV underperform other stocks in the same quintile by −4.60 bps ($t = -2.55$) and the relative underperformance persists for at least

TABLE 8

Regression of Daily Return on Standardized Order Imbalance and Attention Proxies

The dependent variable is the daily return (in bps) on a stock. Each column presents a regression where the dependent variable is the daily return on day $t+1$ in column 1 to the daily return on day $t+5$ in column 5. Retail order imbalance and retail trading activity in the stock are measured on day t. SOI^q_{it} is an indicator variable that take a value of 1 if the stock is in retail order imbalance quintile q, $q = 1, 5$, where quintile 1 contains the stocks most sold and quintile 5 contains the stocks most bought. We omit quintile 3 so coefficients represent variation relative to this omitted category. $HISAV_{it}$ is an indicator variable that takes a value of 1 if the stock is in the top decile of abnormal volume on day t, which we interact with each of the five-order imbalance indicators in Panel A. $HISAAOR_{it}$ is an indicator variable that takes a value of 1 if the stock is in the top decile of abnormal absolute overnight return (from close on day $t-1$ to open on day t), which we interact with each of the five-order imbalance indicators in Panel B. $HISANEWS_{it}$ is an indicator variable that takes a value of 1 if the stock is in the top decile of abnormal news (Dow Jones News Service news mentions) on day t, which we interact with each of the five-order imbalance indicators in Panel C. The computation method of standardized abnormal volume, absolute overnight return, and news is identical to SARV. Robust standard errors are clustered by day. t-statistics are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	$RET_{i,t+1}$	$RET_{i,t+2}$	$RET_{i,t+3}$	$RET_{i,t+4}$	$RET_{i,t+5}$
	1	2	3	4	5
Panel A. High Standardized Abnormal Volume (HISAV)					
$SOI^5_{it} \times HISAV_{it}$	−4.60*	−7.49**	−4.18*	1.99	0.08
	(−2.55)	(−4.14)	(−2.46)	(1.22)	(0.05)
$SOI^4_{it} \times HISAV_{it}$	7.48**	−1.15	2.62*	2.75*	1.62
	(5.03)	(−0.92)	(2.26)	(2.31)	(1.39)
$SOI^3_{it} \times HISAV_{it}$	8.02**	0.88	1.83	2.53*	1.24
	(5.41)	(0.69)	(1.60)	(2.20)	(1.10)
$SOI^2_{it} \times HISAV_{it}$	7.22**	2.17	2.22	2.72**	3.11**
	(5.15)	(1.82)	(1.93)	(2.59)	(2.68)
$SOI^1_{it} \times HISAV_{it}$	3.15*	1.56	2.93*	1.38	1.75
	(2.17)	(1.16)	(2.39)	(1.17)	(1.53)
SOI^5_{it}	3.78**	0.60	0.17	0.18	0.73
	(6.78)	(1.12)	(0.32)	(0.34)	(1.30)
SOI^4_{it}	2.56**	0.89*	0.49	0.16	0.67
	(6.16)	(2.19)	(1.18)	(0.37)	(1.57)
SOI^2_{it}	−1.32**	−0.01	−0.57	−0.74	−0.28
	(−3.25)	(−0.03)	(−1.41)	(−1.78)	(−0.67)
SOI^1_{it}	−2.18**	−0.95	−0.64	−1.29*	−1.24*
	(−4.31)	(−1.89)	(−1.20)	(−2.49)	(−2.36)
No. of obs.	6,824,365	6,819,660	6,814,976	6,810,360	6,805,967
R^2	0.097	0.098	0.099	0.099	0.100
Panel B. High Standardized Abnormal Absolute Overnight Return (HISAAOR)					
$SOI^5_{it} \times HISAAOR_{it}$	−9.63**	−3.50*	−5.81**	1.69	−0.18
	(−4.91)	(−2.09)	(−3.70)	(1.07)	(−0.13)
$SOI^4_{it} \times HISAAOR_{it}$	−0.36	0.35	2.93*	1.13	0.42
	(−0.27)	(0.27)	(2.23)	(0.90)	(0.33)
$SOI^3_{it} \times HISAAOR_{it}$	−1.15	−0.15	1.61	0.93	2.05
	(−0.82)	(−0.12)	(1.24)	(0.78)	(1.73)
$SOI^2_{it} \times HISAAOR_{it}$	−2.41*	0.78	0.58	0.89	2.81*
	(−1.99)	(0.65)	(0.46)	(0.74)	(2.21)
$SOI^1_{it} \times HISAAOR_{it}$	−2.94*	0.87	4.51**	−0.14	−0.12
	(−2.07)	(0.64)	(3.43)	(−0.11)	(−0.09)
SOI^5_{it}	3.60**	0.11	0.30	0.10	0.84
	(6.37)	(0.20)	(0.56)	(0.18)	(1.53)
SOI^4_{it}	2.41**	0.67	0.41	0.20	0.88*
	(5.76)	(1.64)	(1.00)	(0.48)	(2.11)
SOI^2_{it}	−1.28**	0.05	−0.46	−0.66	−0.17
	(−3.11)	(0.11)	(−1.16)	(−1.58)	(−0.41)
SOI^1_{it}	−2.50**	−0.95	−0.84	−1.26*	−0.96
	(−4.96)	(−1.86)	(−1.62)	(−2.47)	(−1.88)
Constant	5.27**	4.95**	4.84**	5.01**	4.37**
	(16.92)	(16.36)	(15.95)	(16.71)	(14.40)
No. of obs.	6,822,781	6,818,078	6,813,393	6,808,778	6,804,385
R^2	0.097	0.098	0.099	0.099	0.100

(continued on next page)

TABLE 8 (continued)

Regression of Daily Return on Standardized Order Imbalance and Attention Proxies

	$RET_{i,t+1}$	$RET_{i,t+2}$	$RET_{i,t+3}$	$RET_{i,t+4}$	$RET_{i,t+5}$
	1	2	3	4	5
Panel C. High Standardized Abnormal News (HISANEWS)					
$SOI^5_{it} \times HISANEWS_{it}$	−13.43**	−6.30**	−3.99**	−0.27	−2.44
	(−7.18)	(−3.67)	(−2.74)	(−0.18)	(−1.77)
$SOI^4_{it} \times HISANEWS_{it}$	0.30	−0.39	−0.31	−0.39	−0.74
	(0.28)	(−0.41)	(−0.32)	(−0.41)	(−0.76)
$SOI^3_{it} \times HISANEWS_{it}$	−1.06	−0.67	−0.51	1.41	−0.41
	(−1.06)	(−0.71)	(−0.57)	(1.56)	(−0.45)
$SOI^2_{it} \times HISANEWS_{it}$	−1.41	−1.77**	1.15	1.07	1.85
	(−1.57)	(−2.05)	(1.24)	(1.22)	(1.64)
$SOI^1_{it} \times HISANEWS_{it}$	−1.91	−2.91**	2.23*	−0.58	0.91
	(−1.90)	(−2.75)	(2.20)	(−0.61)	(0.95)
SOI^5_{it}	3.45**	0.13	−0.31	0.18	0.54
	(5.76)	(0.23)	(−0.56)	(0.33)	(0.93)
SOI^4_{it}	2.40**	0.75	0.66	0.49	0.77
	(5.44)	(1.75)	(1.52)	(1.10)	(1.80)
SOI^2_{it}	−1.39**	0.00	−0.80	−0.73	−0.33
	(−3.24)	(0.01)	(−1.88)	(−1.70)	(−0.78)
SOI^1_{it}	−2.63**	−0.79	−0.83	−1.22*	−1.42**
	(−5.00)	(−1.52)	(−1.54)	(−2.32)	(−2.64)
Constant	4.81**	4.65**	4.65**	4.62**	4.35**
	(15.42)	(15.46)	(15.35)	(15.15)	(14.04)
No. of obs.	6,425,212	6,423,684	6,422,150	6,420,626	6,419,107
R^2	0.104	0.105	0.106	0.107	0.107

another 2 days. In Table A6 in the Supplementary Material, we replace SAV with SARV (arguably a more direct measure of retail attention) and find effects with the same signs but economically bigger in the heavy retail volume decile. These results provide further support for the observation that the trading strategies based on retail order imbalance yield results that are the opposite of those documented in the extant literature when we interact order imbalance with the intensity of trading.

In Panels B and C of Table 8, we replicate the panel regressions described previously replacing SAV with SAAOR and SANEWS as measures of attention.

In Panel B of Table 8, we replace SAV with SAAOR, which is calculated in an analogous fashion to SAV. $HISAAOR_{it}$ is an indicator variable that takes a value of 1 if the stock is in the top decile of abnormal absolute overnight return (from close on day $t-1$ to open on day t). On day $t+1$, stocks in the top order imbalance quintile ($q = 5$) earn 3.60 bps (vs. 3.67 bps in Panel A) relative to the baseline quintile (quintile 3) and stocks in the bottom quintile ($q = 1$) earn −2.50 bps (vs. −2.61 in Panel A). And on day $t+1$, stocks in the top order imbalance quintile and the top decile of SAAOR underperform other stocks in the same quintile by −9.63 bps (vs. −10.07 bps in Panel A).

In Panel C of Table 8, we replace SAV with SANEWS which is calculated in an analogous fashion to SAV (using the daily Dow Jones News Service mentions of a stock). $HISANEWS_{it}$ is an indicator variable that takes a value of 1 if the stock is in the top decile of SANEWS. On day $t+1$, stocks in the top order imbalance quintile ($q = 5$) earn virtually the same return as before 3.45 bps (vs. 3.67 bps in Panel A) relative to the baseline quintile (quintile 3) and stocks in the bottom quintile ($q = 1$) earn -2.63 bps (vs. -2.61 in Panel A). And on day $t + 1$, stocks in the top order imbalance quintile *and* the top decile of SANEWS underperform other stocks in the same quintile by -13.43 bps (vs. -10.07 bps in Panel A).

To summarize, for stocks in the high-order imbalance quintile, returns are negative when stocks (within each quintile) are sorted on three different measures of attention: SAV, SAAOR, and SANEWS. The news measure leads to the most negative returns.

IV. Trade Size and Performance

In Figure 3, we see that the long–short strategies based on retail order imbalance perform well when stocks are weighted equally. These strategies perform poorly when weighted by the dollar value of trade, and the underperformance grows when weighted by the number (rather than dollar value) of trades. The fact that strategies based on the average trade perform worse than strategies based on the average dollar invested suggests that retail investors who place smaller trades underperform, on average, those who place larger trades. This is not surprising since wealthier investors are likely, on average, to execute large trades and prior studies find that wealth and trade performance are positively correlated (Barber and Odean (2000), Li, Geng, and Subramanyam (2017), Campbell, Ramadorai, and Ranish (2019), Jones et al. (2020), and Eaton et al. (2022)).[17] We verify the assertion that wealthier investors place larger trades for a subset of investors with accounts at a large discount brokerage (1991–1996) and report our findings in the Figure A1 in the Supplementary Material. Trade size covaries positively with self-reported wealth, income, investment knowledge, and experience.

We conjecture that the trades of less wealthy, less knowledgeable, and less experienced investors are more likely to be influenced by non-fundamental factors such as attention. Since the trades of these investors tend to be smaller, we expect that small purchases will be more highly concentrated in high-attention stocks. And, to the extent that underperformance of retail trades that we document is attributable to attention, smaller retail trades should underperform larger trades.

To document the distribution of retail trade size, we construct six trade size (TS) bins with the following cutoffs: $\text{TS} \le \$500$; $\$500 < \text{TS} \le \$2{,}000$; $\$2{,}000 < \text{TS} \le \$10{,}000$; $\$10{,}000 < \text{TS} \le \$30{,}000$; $\$30{,}000 < \text{TS} \le \$100{,}000$; and $\text{TS} > \$100{,}000$. The biggest trade size bin represents trades that we previously excluded from our main analysis ($\text{TS} > \$100{,}000$). In Figure 4, we summarize the total proportion of trades that fall into each trade size bin. When measured by the number of trades (black bars), 34% of trades fall into the two smallest trade size bins and about 1.7% of trades fall into the biggest trade size bin (>\$100,000). In contrast, when measured by the value of trades, 31.4% of dollars traded falls into the biggest trade size group.

[17]In contrast, Welch (2022) finds the aggregate holdings of Robinhood investors, who are likely less wealthy and less experienced than the average retail investor, earn strong returns from 2018 to 2020. Relatedly, trades at retail brokers outperform trades at a discount broker in Australia (Fong, Gallagher, and Lee (2014)) and trades of high IQ investors outperform other retail investors in Finland (Grinblatt, Keloharju, and Linnainmaa (2012)).

FIGURE 4

Proportion of Trade by Trade Size Categories

We construct six trade size bins with cutoffs at $500, $2,000, $10,000, $30,000, and $100,000. Figure 4 depicts the percent of retail trades that fall into each trade size bin by number of trades (black bars) and value of trades (gray bars).

A. Trade Size and the Concentration of Buying in High-Attention Stocks

To investigate whether small retail trades are more concentrated in high-attention stocks, we use SAV, SAAOR, and SANEWS as proxies for attention. For each day, we calculate the percent of all small buys (i.e., trades < $500) that are concentrated in stocks in the top quintile of SOI (SOI quintile 5) and the top SAV decile. This generates a time series of daily percentages from which we calculate an average daily percentage. This calculation is repeated for small sells. There is an analogous calculation of the two statistics for the other trade size bins. We then repeat this analysis for SAAOR and SANEWS.

In Graph A of Figure 5, we graph the concentration of buying and selling in attention-grabbing stocks (as measured with SAV) within each of the trade size bins. There is a clear pattern for buying. Small purchases are disproportionately concentrated in the attention-grabbing stocks that earn poor subsequent returns. For small purchases, 11.68% of all trades are concentrated in these stocks compared to 7.42% for big purchases. In contrast, we do not observe as distinct a pattern for sales, which is 7.42% for small trades to 7.33% for big trades.[18] The results are similar when attention measures are based on overnight returns (Graph B of Figure 5) or news (Graph C of Figure 5).

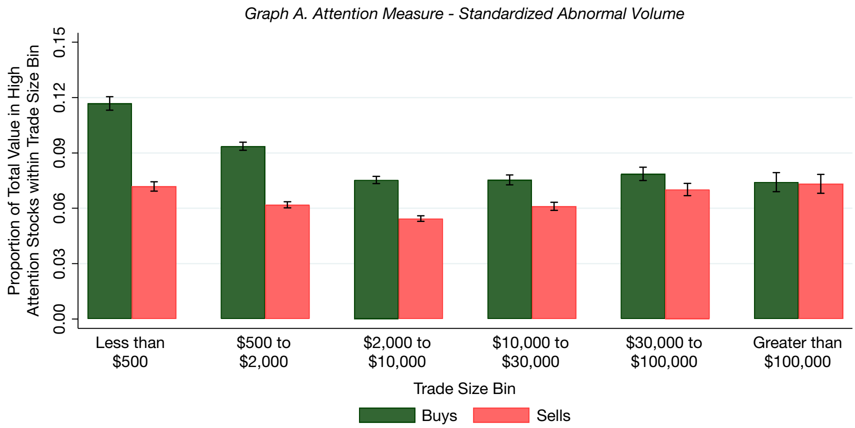
The concentration of small purchases in these attention-grabbing stocks indicates that small traders are more likely than big traders to purchase stocks that capture their attention. The lack of differences in the concentration of sales is consistent with the theory that attention is less of a factor in sales decisions, since retail investors tend to only sell that which they own and small investors tend to invest in only a few stocks (Barber and Odean (2000), Goetzmann and Kumar (2008)).

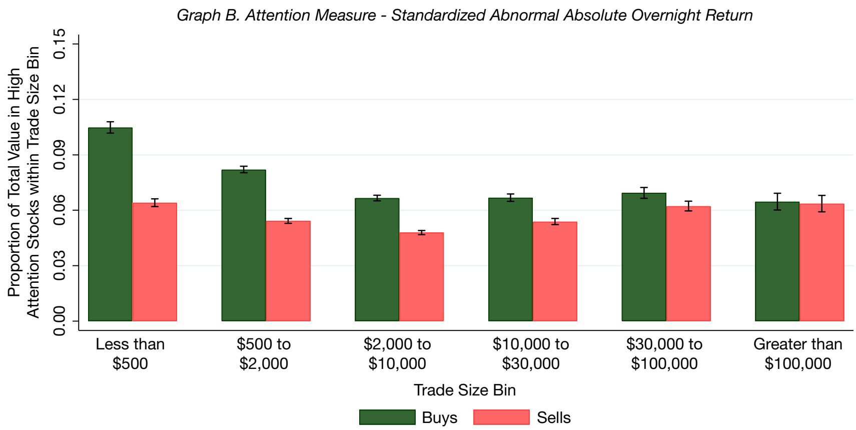
[18]In Figure A3 in the Supplementary Material, we observe similar patterns using standardized abnormal retail volume.

FIGURE 5

Percent of Buy Versus Sell Value in Attention-Grabbing Stocks by Trade Size Bins

Within each trade size bin, the bars in Figure 5 show the mean daily percent of the total value of buys (or sells) that occur in stocks in the top retail order imbalance quintile (SOI quintile 5) and the top decile of attention measures. Graph A measures attention with standardized abnormal volume (SAV), Graph B uses standardized abnormal absolute overnight return (SAAOR), and Graph C uses standardized abnormal news (SANEWS). Whiskers represent 95% confidence intervals.





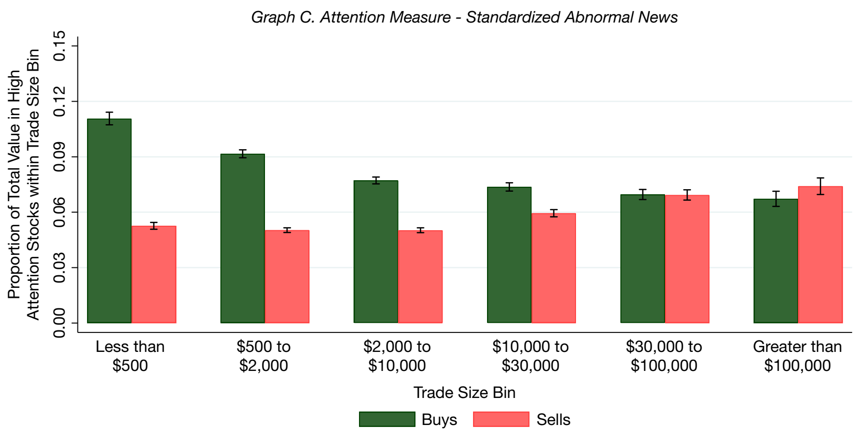
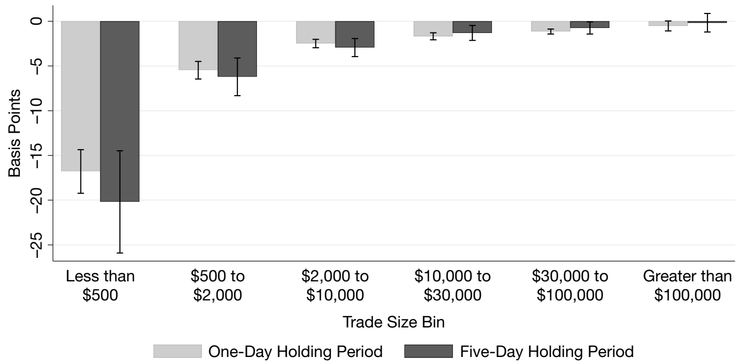


FIGURE 6

Return on Stocks Bought Minus Stocks Sold by Retail Investors by Trade Size Bin

Figure 6 shows the return spread on a long–short strategy that buys stocks in proportion to retail purchases and sells stocks in proportion to retail sales within each trade size bin. Abnormal returns are calculated as the intercept of the regression of the long–short return on the Fama–French 5-factor model plus a momentum factor. Gray (black) bars depict the cumulative alpha from the transaction on day t to the close of day $t + 1$ ($t + 5$). Whiskers represent 95% confidence intervals.



B. Trade Size and Performance

To test whether performance varies with trade size, we calculate the dollar-weighted returns on buys and sells within each trade size bin and vary the holding period from 1 to 5 days (as in Table 4). In Figure 6, we summarize the spreads on the purchase-weighted returns of stocks bought less the sales-weighted returns of stocks sold within each trade size bin. The smallest trade size bin experiences losses of 16.8 bps at a 1-day holding period and these losses grow to 20.2 bps at a 5-day holding period. In sharp contrast, the biggest trade size bin has much smaller losses at a 1-day holding period (0.5 bps though statistically significant at the 1% level), which shrink to a statistically insignificant 0.2 bps at a 5-day holding period. It is noteworthy that even the largest trades do not profit from trading, either.

To summarize the evidence, small retail trades are more likely to be made by less wealthy and less sophisticated investors, small purchases are more highly concentrated in attention-grabbing stocks, and small trades perform worse than large trades. While not conclusive, these results are strongly consistent with a pattern of less wealthy and sophisticated retail investors engaging in attention-based buying and losing money as a result.

V. Conclusion

We reconcile two well-established yet seemingly contradictory empirical findings: i) in the short-term retail traders underperform, and ii) retail trade order imbalance positively predicts short-term returns. Two key observations explain the paradox. First, retail buying is highly concentrated in trades that perform poorly. Order imbalance studies evaluate hypothetical equal-weighted portfolio strategies, not the actual returns retail investors earn on trades. Thus, the trades of retail investors can be interpreted in a way that positively forecasts returns even though these trades negatively impact retail investor performance. Second, retail performance is quite poor on the day trades execute, especially so for the stocks retail investors most aggressively buy.

We speculate that the underperformance of retail trades is related to attention-based trading. Both on the day of trade and over the following days, the purchases of retail investors perform worst when retail order imbalance is high and retail trading volume is high. This is consistent with the theoretical prediction that retail investors will be heavily on the buy side of the market when stocks catch their attention and that this buying will lead to temporary price increases followed by reversals (Barber and Odean (2008)) and with an emerging empirical literature that links attention-grabbing events to subsequent negative abnormal returns.[19]

We also find that small trades, which tend to be made by less wealthy, less experienced, and less sophisticated investors are more concentrated in attention-grabbing stocks and perform worse than large trades.

Several explanations have been offered for both the negative effect of trading on retail investor performance and the positive signal from retail order imbalance. These explanations are not mutually exclusive.

Many retail investors may make wealth-reducing trades because they do not realize that they are at an informational disadvantage and expect their trades to perform well; in other words, they are overconfident in their ability to trade (Odean (1998) (1999), Barber and Odean (2000) (2001), Statman, Thorley, and Vorkink (2006), and Glaser and Weber (2007)). Retail investors may also make wealth-reducing trades because they find trading entertaining (Dorn and Sengmueller (2009), Luo and Subrahmanyam (2019)), have an urge to gamble (Barber, Lee, Liu, and Odean (2008), Dorn and Sengmueller (2009), Kumar (2009), Gao and Lin (2015), and Dorn, Dorn, and Sengmueller (2015)), are sensation seeking (Grinblatt and Keloharju (2009)), or hope to gain social status by selectively reporting their performance (Hong, Jiang, Wang, and Zhao (2014)).

Retail order imbalance may positively forecast short-term returns due to informed individual investor trading (Kaniel, Liu, Saar, and Titman (2012), Kelley and Tetlock (2013), and Boehmer, Jones, Zhang, and Zhang (2021)), because they are rewarded for providing liquidity to institutional investors (Kaniel, Saar, and Titman (2008), Kaniel, Liu, Saar, and Titman (2012), and Barrot, Kaniel, and Sraer (2016)), or because their order imbalance is positively autocorrelated and thus forecasts short-term price pressure on stock prices (Barber, Odean, and Zhu (2008)). While the informed trading of some retail investors, the willingness of others to provide liquidity, and serially correlated order imbalance may contribute to the short-term predictiveness of retail order imbalance, our results confirm that, on average, retail investors do not profit from trading. Retail trades positively predict returns but are not profitable.

[19]For example, scholars have analyzed Cramer's Mad Money (Keasler and McNeil (2010), Bolster, Trahan, and Venkateswaran (2012), and Engelberg, Sasseville, and Williams (2012)), the WSJ Dartboard Column (Barber and Loeffler (1993), Liang (1999)), Google stock searches (Da, Engelberg, and Gao (2011), Da, Hua, Hung, and Peng (2022)), repeat news stories (Tetlock (2011)), and the trading of Robinhood investors (Barber, Huang, Odean, and Schwartz (2021)).

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Appendix. Analyzing the Gains from Trade

In general, the portfolio return (R_{pt}) on an investor's portfolio is the weighted average of the returns on the stocks that she holds:

$$R_{pt} = \sum_{i=1}^{N} w_{it} R_{it}, \tag{A-1}$$

where the weights, w_{it}, sum to 1. In typical settings, one can think of the returns as daily stock returns and weights are determined by shares held in each security:

$$w_{it} = \frac{S_{it} P_{it}}{\sum_i S_{it} P_{it}}. \tag{A-2}$$

Assume an investor considers trading in the portfolio and stocks bought are financed by selling stocks in the portfolio, thus changing the weights on the various securities in the portfolio. To calculate the gains from trade, one can compare the returns of a counterfactual portfolio that assumes no trading (R_{pt}) to the returns earned on a portfolio that engaged in trading to change some of the security weights (R_{pt}^T)

$$R_{pt}^T - R_{pt} = \sum_{i=1}^{N} w_{it}^T R_{it} - \sum_{i=1}^{N} w_{it} R_{it} = \sum_{i=1}^{N} \left(w_{it}^T - w_{it} \right) R_{it}, \tag{A-3}$$

where $\left(w_{it}^T - w_{it} \right) > 0$ indicates that stock i has been purchased and $\left(w_{it}^T - w_{it} \right) < 0$ indicates that stock i has sold.

$$w_{it}^T - w_{it} = \frac{S_{it}^T P_{it}}{\sum_i S_{it}^T P_{it}} - \frac{S_{it} P_{it}}{\sum_i S_{it} P_{it}}. \tag{A-4}$$

Note that, since the purchases are financed by sales, $\sum_i S_{it}^T P_{it} = \sum_i S_{it} P_{it}$. Define $\Delta S_{it} = \left(S_{it}^T - S_{it} \right)$. Thus,

$$\begin{aligned} R_{pt}^T - R_{pt} &= \sum_i \left(\frac{\Delta S_{it} P_{it}}{\sum_i S_{it} P_{it}} R_{it} | \Delta S_{it} > 0 \right) + \sum_i \left(\frac{\Delta S_{it} P_{it}}{\sum_i S_{it} P_{it}} R_{it} | \Delta S_{it} < 0 \right) \\ &= \frac{1}{\sum_i S_{it} P_{it}} \left[\sum_i \left(\Delta S_{it} P_{it} R_{it} | \Delta S_{it} > 0 \right) + \sum_i \left(\Delta S_{it} P_{it} R_{it} | \Delta S_{it} < 0 \right) \right]. \end{aligned} \tag{A-5}$$

In the right-hand side of equation (A-5), the left summation represents the additional portfolio return that can be traced to stocks bought ($\Delta S_{it} > 0$) and the right summation represents the additional portfolio return that can be traced to stocks sold ($\Delta S_{it} < 0$).

Now consider the dollar-weighted return on a portfolio that mimics the buys (R_{pt}^b) or sells (R_{pt}^s) of the investor:

$$\text{(A-6)}\qquad R_{pt}^{b}-R_{pt}^{s}=\sum_{i}\left(\frac{\Delta S_{it}P_{it}}{\sum_{i}\Delta S_{it}P_{it}}R_{it}|\Delta S_{it}>0\right)-\sum_{i}\left(\frac{-\Delta S_{it}P_{it}}{\sum_{i}\Delta S_{it}P_{it}}R_{it}|\Delta S_{it}<0\right)$$
$$=\frac{1}{\sum_{i}\Delta S_{it}P_{it}}\left[\sum_{i}(\Delta S_{it}P_{it}R_{it}|\Delta S_{it}>0)+\sum_{i}(\Delta S_{it}P_{it}R_{it}|\Delta S_{it}<0)\right].$$

Since purchases are financed by sales, $\sum_{\mathrm{i}}(\Delta S_{it}P_{it}|\Delta S_{it}>0)=\$\$-\sum_{\mathrm{i}}(\Delta S_{it}P_{it}|\Delta S_{it}<0)$. We can summarize the relation between the effect of trading on the portfolio return as

$$\text{(A-7)}\qquad R_{pt}^{T}-R_{pt}=\frac{1}{2}\frac{\sum_{i}|\Delta S_{it}P_{it}|}{\sum_{i}S_{it}P_{it}}\left(R_{pt}^{b}-R_{pt}^{s}\right)=\mathrm{TO}_{t}\left(R_{pt}^{b}-R_{pt}^{s}\right),$$

where TO_t is the period t turnover of the portfolio.

In summary, when purchases and sales are equal, one can assess whether trading improves a portfolio return by analyzing the sign of the spread between the return on a purchase-weighted portfolio and sales-weighted portfolio. The magnitude of the effect on the portfolio return will be determined by portfolio turnover.

Supplementary Material

To view supplementary material for this article, please visit http://doi.org/10.1017/S0022109023000601.

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