When Retail Meets Informed: How News Days Drive Retail Losses

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Abstract

Using recent trader-level data, we examine how news events affect retail behavior and performance. News attracts retail investors, whose activity doubles on news days. Strikingly, this news-driven trading explains all retail stock trading losses in our data. Retail traders lose 13 basis points per trade on news days while earning near-zero returns on no-news days. These losses result from adverse selection as retail investors trade against informed participants, particularly short sellers, skilled at interpreting news. Consistent with this adverse selection channel, retail losses disappear when trading index ETFs on macro news days where private information is scarce; while news-induced losses are particularly large in equity options, where information asymmetry is most severe. Finally, retail investors never learn to avoid this costly pattern. Our findings suggest that news-driven adverse selection has become the major source of retail underperformance in today's zero-commission, media-saturated trading environment.

Keywords and Phrases: Retail trading, option trading, news, sophisticated investors
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1 Introduction

Modern financial platforms and media bombard retail investors with a continuous stream of real-time news, alerts, and commentary, prompting frequent trading. Brokerage platforms frame this development as a democratization of finance, intended to level the informational playing field. But does this constant access to news empower retail investors to profit, or does it expose them to a more subtle and costly form of exploitation? Historically, research attributed retail losses to high transaction costs and behavioral biases like excessive trading (e.g., Odean, 1998, 1999). However, these traditional channels matter less in today's world of low-cost zero-commission trading and increased market efficiency. This prompts us to investigate whether information processing rather than trading costs drive retail underperformance.

Prior research on this topic has been limited by a lack of detailed, recent retail data. We overcome this obstacle with a unique dataset tracking 2.4 million stock and option round-trip trades from over 5,000 retail investors between 2020 and 2022. Sourced from a trading journal, these data contain verified retail trades across multiple brokers. Net returns are reported after all costs, allowing us to isolate the effect of trading decisions and costs on performance. We merge the granular trade data with the RavenPack news database to precisely identify the timing of scheduled and unscheduled corporate news. This combined dataset enables us to measure how individuals respond to news and to quantify the resulting profits or losses. The short holding periods typical of modern retail trading facilitate identifying news-induced trading.

First, we test whether news drives retail trading. Consistent with prior research (e.g., Barber and Odean, 2008), we find that retail trading activity effectively doubles on days with significant corporate news. This surge in activity is robust to controlling for concurrent volatility and trading volume, which also attract retail trading. The news-induced trading is particularly strong for news released right before or during market hours, when investors pay attention and can react immediately, and is nearly as pronounced for unscheduled news as for earnings announcements.

As for performance, news-driven trading is disastrous for retail investors. It explains *all* of their aggregate trading losses in our sample, even though news days constitute only 14% of all retail trading days. Retail investors break even on non-news days and lose about 13 basis points per trade, on average, relative to no-news days. Our findings are robust and persist even after we

control for return, trading volume, and volatility differences, and the inclusion of firm and investor fixed effects. It applies regardless of the news's sentiment, and affects both large and small trades. Furthermore, the timing of new releases and retail trades aligns. Retail trading volume surges within the first hour of a news release, and intraday analysis confirms their losses are sharpest in this immediate aftermath. Also, while we focus on regular news, social media is often considered an alternative news source, often covering events overlooked by regular media. Retail losses are similar on regular news days and days with high social media chatter for a given stock. These findings challenge the narrative that democratized finance necessarily empowers retail investors.

To explain these retail losses, we study the traders on the other side of the transaction: informed professionals. We examine the behavior of short sellers, a well-documented group of informed traders (Cohen, Diether, and Malloy, 2007; Engelberg, Reed, and Ringgenberg, 2012), using short-sale transaction data from FINRA. Indeed, days with high shorting activity are followed by -19 bps returns next day and -90 bps return next month. Similar to retail activity, short sellers flock to news, and their trading activity is normal pre-news, but spikes in the moments after a story breaks. Importantly, their post-news trades strongly predict future negative returns, implying they successfully interpret the new information. In fact, their news-day activity predicts returns stronger than their activity from no-news days.

We next study how these two groups interact and find that retail losses directly track short-seller activity. When short sellers trade most aggressively, retail investors incur 8 bps higher losses on no-news days and even higher 17 bps losses on news days. In these moments, the market becomes a zero-sum game, and retail investors are consistently on the losing side and are funding the profits of informed professionals, who exploit the information in the news. In contrast, retail investors break even on days (including news days) when short sellers are not particularly active, and retail investors only lose around news if they trade in the direction opposite of short sellers.

To sharpen this interpretation, we study two alternative environments with lower and higher adverse selection, respectively. First, we study trading around major macroeconomic news where information advantages are relatively small. We analyze retail trades in broad market index ETFs on days with the five most important macroeconomic releases, including FOMC announcements and Nonfarm Payroll reports. Retail investors break even around these events; in fact, return estimates are positive but not statistically significant. When the informational playing field is

level and private information is scarce, retail investors trade on equal footing as reflected in their performance. Second, we study retail trading in the options market. We expect new-induced retail losses to be larger in the options market, where information asymmetries are notoriously high. Indeed, retail investors' option trades lose 2% more on news days, a substantial penalty driven by the heightened presence of informed traders. These losses are even higher on days when informed investors are particularly active. Thus, retail losses are most severe in the very markets where informed trading is most prevalent.

Our findings validate classic theories in the context of the modern, high-speed trading environment. Kim and Verrecchia (1994) show that divergence in beliefs (and thus trading activity) spikes upon public news arrival, while Kyle (1985); Glosten and Milgrom (1985) predict that informed traders profit at the expense of uninformed "noise" traders due to adverse selection. We show this process in action. News events attract retail investors and short sellers. They also intensify information asymmetry, turning retail investors into the noise traders who fuel the profits of the informed. The sharp contrast in retail performance between news and no-news days shows that the information environment, not a general lack of skill, dictates whether they win or lose.

Behavioral economics debates whether investors can learn to overcome costly biases (Barber and Odean, 2000; Seru, Shumway, and Stoffman, 2010). We therefore test whether the investors in our sample, who are sophisticated enough to use a trading journal, learn from their repeated negative experiences on news days. By tracking individual trading histories, we find no evidence of such learning. The performance penalty for trading on news does not diminish with experience; an investor's 100th news-day trade is, on average, just as unprofitable as their first. This shows that the impulse to trade on exciting news is a powerful habit that repeated losses cannot cure.

Leveraging our detailed account-level data, we show our main result is not driven by a single type of retail investor. The traders in our sample are highly heterogeneous, with styles ranging from high-frequency day traders to longer-term swing traders. Yet, the central finding holds: news-driven trading is consistently costly across all major trading styles, regardless of trade frequency, holding period, or typical trade size. For example, while the losses are pervasive, they are most severe for the least sophisticated, as proxied by trade size. Smallest size traders lose 0.92% on news days, much more than the 0.12% average. This robustness underscores that the adverse selection problem on news days is a fundamental feature of the market environment, affecting a wide spectrum of

individual investors.

We acknowledge that our dataset, while detailed, captures a specific slice of the retail population. Journal users whom we study are likely more active, sophisticated, and performance-conscious than the average retail trader. This selection, however, likely strengthens our conclusions rather than weakening them. If these relatively sophisticated traders systematically lose money by trading on news, less-sophisticated retail population likely fares even worse. Therefore, our estimates of news-driven losses likely represent a lower bound on the true costs faced by the typical retail investor.

Our findings challenge regulators, platform designers, and investors. We provide an example that democratized market access does not necessarily empower investors; rather, high-salience news may trap them in costly trades. Regulators and platform designers can do more to scrutinize platform designs that amplify news and facilitate a predictable wealth transfer from individuals to institutions. For investors, our work proves that interpreting information correctly is far more valuable than merely accessing and reacting to it.

Related Literature: Our paper contributes to several distinct, yet interconnected, strands of literature. First, we build on the extensive literature on retail investor behavior and performance. Prior work establishes that individual investors often trade excessively, are drawn to attention-grabbing stocks, and systematically underperform (e.g., Odean, 1999; Barber and Odean, 2000, 2008; Barber, Lin, and Odean, 2024). We identify a new underperformance mechanism: the response to public news. Unlike other salient events (such as extreme returns or high trading volume) news carries new information that urges retail trading. Using granular, verified trader-level data, we quantify the cost of this behavior and show that news-driven trading accounts for virtually all losses in our sample. Also, we focus on sophisticated retail investors using analytical tools, complementing studies on novice investors (e.g., Barber, Huang, Odean, and Schwarz, 2022), and show that even they fall prey to costly news-driven trading. Finally, retail investors are typically studied in isolation, while we directly study how they interact with informed investors, such as short sellers.

Second, our findings also speak to the broader debate on the democratization of retail investing. Improvements in information technology and the proliferation of social media platforms have eased retail investors' access to news. One growing view argues that these improvements help narrow the informational gap between individual and institutional participants. Gao and Huang (2020) show that following EDGAR implementation, retail trades become more informative about future

stock returns. Farrell, Green, Jame, and Markov (2022) show that access to information on social media (SeekingAlpha) has improved the ability of retail order imbalances to predict returns and cash-flow news. Cookson, Lu, Mullins, and Niessner (2024a) show that social media sentiment is associated with retail trading and positively predicts subsequent returns. Adding to this debate, our findings show that while easier access to news enables retail investors to react more quickly, this exposes them to adverse selection by better-informed market participants. We find that losses on news days are nearly three times larger when retail investors trade in the direction of the news, and are particularly pronounced on days with elevated short-selling activity.

Second, we contribute to the literature on how public information is processed and incorporated into asset prices by different groups of market participants. Previous research shows that sophisticated investors profit not by trading on private signals, but by interpreting public information more effectively (e.g., Engelberg et al., 2012; Huang, Tan, and Wermers, 2020). We extend this insight by simultaneously analyzing the actions of both informed and less informed traders in response to the same public signals. We find that news acts as a double-edged sword: it attracts less informed traders (retail) while creating profitable trading opportunities for those who can better interpret it (short sellers). Our finding that retail investors do not learn to avoid these costly trades, despite repeated negative feedback, adds to the literature on investor learning (or lack thereof) and highlights the powerful and persistent nature of attention-based trading biases (Seru et al., 2010).

Finally, we provide a new empirical test of classic adverse selection models and belief updating frameworks in the context of public news. Theoretical frameworks of Kyle (1985) and Glosten and Milgrom (1985) posit that informed traders profit from the presence of uninformed "noise" traders, particularly when information asymmetries are high. Our study illustrates this process. By showing that retail losses peak precisely when informed short sellers are most active following news releases, we document the wealth transfer these models predict. One key contribution is to compare firm-specific news, where information asymmetry is high, to macroeconomic news, where it is low. The finding that retail losses vanish in the macro setting indicates that adverse selection, and not a general lack of skill, is the primary driver of the losses we document.

2 Data and Summary Statistics

2.1 Media coverage

We identify news media events via RavenPack 1.0, focusing on news events that carry fundamental information (Boudoukh, Feldman, Kogan, and Richardson, 2019). We use RavenPack classifications of news events and timestamps. Following Reed, Samadi, and Sokobin (2020), we retain articles with a relevance score of 100 (i.e., the firm is the main subject of the article), and focus on thirteen news categories that were found in prior literature as fundamental. We then keep news with event relevance score or 100, which ensures that the news category is mentioned in the headline of the article. Finally, news that occurs after the market close is shifted to the next trading day.

We construct a news dummy variable (*NEWS*) that receives a value of 1 if there is at least one news article covering the firm on a given day across the selected categories and 0 otherwise. Similarly, we construct a set of dummy variables for news that occur after market close (4:00 pm - 11:59 pm of day t-1), before market open (12:00 am to 9:30 am of day t) and during trading hours (9:30 am to 4:00 pm of day t).

3 Results

3.1 Summary stats

Table 1 reports summary statistics conditioning on news events. We report statistics at the stock-day (Panel A) and stock-day-trade (Panel B) level. In particular, we split the sample into news and non-news days and report the averages of key variables of interest, together with their standard errors, and cross-sample differences.

Panel A indicates that the average daily number of trades (aggregated across all accounts) on news days is almost double the amount of trading on non-news days (11.03 vs. 6.20). Volatility is also higher on news days, where the absolute return on news days (non-news days) is 10.33% (6.73%). Interestingly, liquidity is also higher on news days, measured by turnover, the effective spread, and Kyle Lambda. This is consistent with proir literature, which reveals that retail investors' trading improves liquidity. The fact that liquidity is higher on news days suggests that retail investors are not concerned about adverse selection, as they participate more intensively on these days. For example, the average (median) effective spread on news days is 0.276%(0.104%) in

comparison to spreads on non-news days 0.346% (0.171%).

[Table 1]

Panel B reports statistics at the trade level. The univariate statistics indicate that retail investors earn substantially lower returns on trades made on news days relative to non-news days. Taking into account all sample trades, the average net trade gain (NTG) in basis points on news days (non-news days) is 0.766 (13.81) basis points. Focusing on trades made after signing up for the journal (which removes a positivity bias) indicates that the average NTG on news days is -8.26 basis points, relative to an average of 1.12 basis points on non-news days. Exploring the trade duration indicates that the duration of trades that coincide with news days is shorter than other trades. Using daily indicators, the duration of a trade on news days is 1.18 days relative to 2.069 on non-news days. In a similar manner, using a subsample of trades that include intraday timestamps, we find that the duration in minutes on news days is 25.82 minutes relative to 31.93 on non-news days.

3.2 Retail trading intensity around news

We explore how retail investors trade in response to news and other known attention triggers. We focus on the stock-day sample, where we regress the daily number of trades (aggregated across all accounts) on news dummy indicators, earnings day indicator, and other control variables. Two well-known attention triggers are returns and trading volume. Thus, we include in our regressions day's t absolute returns and abnormal trading volume (using day t'v volume relative to its 63-day rolling average). In addition, we control for liquidity using day t's effective spread, past returns, average turnover, market capitalization, standard deviation of returns, Amihud liquidity measure, and institutional holdings. Our specifications include date and firm fixed effects.

[Table 2]

Across all specifications, news is associated with heightened trading ranging from 2.316 to 6.805. Controlling for other attention triggers and firm characteristics, the coefficient estimate of *NEWS* is about 2.4, which is about 33% higher than the non-news benchmark reported in Table 1A (7.276). Decomposing the effect of *NEWS* to the time of news arrival indicates that retail investors respond

to news that occurs before market open (*BMO_NEWS*) and during market hours (*DMH_NEWS*). The effect of one standard deviation changes in absolute returns and abnormal trading volume is about 6.4 and 9.8, respectively (Panel A of Table IA.2). But, this is expected since trading volume and returns are contemporarily measured with the accounting activity. Finally, the additional effect of earnings announcements (*EDAY*) relative to all news is positive but insignificant.

Next, to provide another perspective, we explore both the daily and intraday intensity of trading around news events. At the daily level, for each stock j and news day t, we construct a seven-day window from day t-3 to t+3. We then calculate the percentage fraction of each day relative to the total trades in a given window, net of the firm's expected benchmark. The benchmark is calculated using all non-news trades of stock j and the day-of-the-week of the news day. Panel A of Table 3 reports the results. We can clearly observe that the trading intensity on news days (day t) is 43.24% higher relative to the random benchmark, where other days around the event exhibit lower trading intensity, with negative values relative to the random benchmark. Table IA.1 reports similar results for earnings days, where earnings days exhibit an increase of 58.44% relative to the random benchmark.

[Table 3]

In a similar manner, Panel B reports the intraday trading intensity around the time of the news release net of the firm's expected benchmark. Trade timestamps are available for a subset of 551,342 trades (out of 1,466,303 trades). For each day and news event category, we keep the first timestamp at which the news appeared on RavenPack and define it as time 0. We keep all trades in a window of three hours [h-3, h+3] and require at least one trade. We then calculate the percentage fraction of trades in each hour relative to the total number of trades in that window. Similar to Panel A, we construct a benchmark based on all stock trades on non-news days in similar windows around the same intraday time stamp adjusted for the day-of-the-week.

Interestingly, retail investors are attentive to news, where the trading intensity is the highest in the second hour after the news becomes public on RavwenPack. The intensity in the first (second) hour of the news release is about 7.42% (11.23%) higher, relative to a random intraday benchmark. Finally, the trading subsides around the third hour, with an abnormal intensity of 2.85%. Exploring earings days (Table IA.1), we find more persistence where the trading intensities in hours 1-3 are

5.5%, 11.11%, and 17.15%, respectively.

3.3 Retail Performance on News Days

Next, we explore the trade performance of retail investors on news days relative to non-news days, controlling for other attention triggers and firm characteristics. We conduct our analysis at the stock-day-trade level. The explanatory variables and controls are similar to those reported in Table 2. We include firm and account ID fixed effects.

In Columns 1-5, we explore the relation between net trade gain in percent and *NEWS*. Across all specifications, news days are associated with trade performance that is -0.119% to -0.134% lower than non-news days. Decomposing *NEWS* we find that the negative relation is concentrated in *BMO_NEWS* and *DMH_NEWS*, with coefficient estimates of -0.078% and -0.134%, respectively. This is consistent with retail investors being adversely selected during regular trading hours, when they can react quickly to the news.

[Table 4]

To contrast the performance on news days to other attention triggers, Panel B of Table IA.2 reports the effect of a one standard deviation change in absolute returns and abnormal trading volume. For example, Column 4 indicates that the standardized effect of absolute returns (abnormal trading volume) is about -0.078% (0.045%). However, the effect becomes insignificant once we include account ID fixed effects.

Next, we extend the analysis conducted in Table 4 by exploring subsamples based on trade type and the direction of daily returns. We find the negative relation between *NEWS* and net trade gain is concentrated in long position trades with a coefficient estimate of -0.241%. Moreover, it is more pronounced when retail investors buy on days with positive returns, which account for most of the long position trades. This suggests that retail investors do not act as contrarians, but rather buy on news to reflect their information. However, they seem to be adversely selected.

[Table 5]

In the final set of tests of this section, we are interested in exploring the trade duration conditioning on news days. We find that on news days, retail investors close their positions about

6 minutes quicker when firm fixed effects are included and 4 minutes quicker when account ID fixed effects are included. Splitting based on the time of news, we find that this relation is most pronounced for news during market hours. Interestingly, this overlaps with the time when retail investors face the largest losses from trading.

[Table 6]

In a non-tabulated result, we further split the sample into long and short positions. We find that the trade duration effect is the strongest for long positions, and when the trade is in the direction of the daily returns. Overall, it seems that the losses of retail trades on news days are also associated with a shorter trading horizon. One explanation is that retail traders cut their losses and close their positions quickly (i.e., an endogenous decision based on the outcome). Another one is that this is a trader characteristic in which some trade aggressively and some trade slowly.

3.4 Trading Against sophisticated Investors

The model in mind is based on retail overconfidence + adverse selection. In traditional models, adverse selection leads to lower liquidity. Here, liquidity is better on information arrival days. This suggests that retail investors are not worried about getting picked up, which is consistent with retail overconfidence. Our learning analysis suggests that retail investors do not learn from past experience, which can be another indication of overconfidence and why liquidity increases. After establishing the SS result, the social media tests show that news (knowledge) differs from mere attention.

Short-sellers have been identified in the literature as skilled information processors, with their ability to react quicker on public news arrival (Engelberg et al., 2012). Thus, in this section, we use short-selling intensity to investigate whether retail investors are adversely selected by other sophisticated investors. We obtain short-selling volume data from FINRA's website. For each firm, we aggregate the short-selling volume at the daily level and normalize it by the number of outstanding shares. We then rank the normalized short-selling measure into terciles (SS_TER), where tercile 3 (1) captures high (low) short-selling intensity. The number of regression observations is based on the intersection of both data sets.[1]

[1]In Table IA.3 we validate FINRA's short-selling data by exploring the relation between FINRA's short-selling data and subsequent stock returns. Consistent with the literature, we find a negative and statistically significant relation.

[Table 7]

Table 7 report the findings, where we include *NEWS*, together with *SS_TER* and their interaction. All specifications include firm and account ID fixed effects. Columns 1-3 report the results for all trades. *NEWS* coefficient estimate for the short-selling sample is -0.149%. Including *SS_TER*, we find that an increase in short-selling activity by 1 tercile is associated with a lower trade performance of about -0.086%. Importantly, the interaction between *NEWS* and *SS_TER* is negative and statistically significant, which is consistent with trading losses on news days when short-selling activity is high.

Splitting the sample into long and short trading positions, we find that retail investors' losses to short-sellers are concentrated when retail investors buy. The effect is sizable, and the interaction term suggests that a change in SS ranking by one tercile on news days results in a reduction of -0.19% in trade performance.

Our analysis uses traditional news to explore how retail investors trade on information. With the growing importance of social media, a natural question to ask is whether social media affects retail trading and retail investor trading against better-informed investors. For example, heightened social media can deter short-sellers if they believe that this can result in persistent non-fundamental price effects.

We obtain social media data from Cookson, Lu, Mullins, and Niessner (2024b), and measure social media attention following Cookson et al. (2024b) as the daily abnormal number of user messages on social media of firm j on day t. Abnormal social media activity is calculated as day t's number of user messages relative to its 3-month rolling average. We rank the measure into terciles (*SM_TER*), where tercile 3 (1) captures high (low) social media attention.

[Table 8]

We explore the relation between *NEWS*, social media, and short-selling activity in Table 8. Columns 1–2 are based on the social media sample. Columns 3–8 are based on the intersection of the social media and FINRA's short-selling samples. We include firm and account ID fixed effects in all specifications. Column 1 presents the base result, where trade performance is lower by -0.175% on news days. Column 2 indicates that the inclusion of social media attention (*SM_TER*)

slightly reduces the news effect, with a coefficient estimate of -0.141%. The social media, in turn, is negative (-0.06%) but statistically insignificant.

Next, Column 3 indicates that *NEWS* is associated with a lower trade performance of -0.285%. Including social media (Column 4), the *NEWS* coefficient estimate is about -0.25%. Interestingly, social media is negative and statistically significant in the short-selling sample, with a coefficient estimate of -0.106%. However, including the short-selling ranking (*SS_TER*) attenuates the social media effect, which becomes insignificant. Finally, columns 6-8 focus on the interactions of *NEWS* and *SM_TER* with *SS_TER*.

3.5 Validation Tests

We validate our findings using two settings. First, we repeat our analysis for option trades, where information asymmetry should be higher. Second, we repeat our analysis using macro events where information asymmetry is low.

We explore the profitability of stock option trades (net trade gain) on news days. Given the skewed retail interest in stock options, we exclude the top 10 heavily traded stock options. We conduct our analysis at the security-day-trade level. Panel A repeats the analysis conducted in Table 4. overall, the results are consistent with our equity trading findings. Given that stock options have an inherent leverage, we find larger magnitudes. In particular, retail investors' performance is about 2% lower on news days. Interestingly, we find that this is concentrated in cases where news arrives after market close of the previous day (*AMC_NEWS*) and during market hours (*DMH_NEWS*).

Panel B repeats the analysis conducted in Table 5 where the trades are split based on trade type and the sign of the daily returns. Consistent with our equity findings, retail investors' lower performance is concentrated in long positions, which account for 80.3% (=226,930/282,536) of options' trades. Moreover, we find negative and significant results for positive and negative returns. One interesting finding is that we find that retail investors earn higher performance on news days for short positions accompanied by negative daily returns. This suggests that some retail investors benefit from trading on news these days.

[Table 9]

Finally, Panel C repeats the analysis conducted in Table 7. Again, we find consistent results with those reported for stock trades. For the joint short-selling sample, Columns 1-3 indicate that

retail investors lose about 1.6% on news days relative to non-news days. The presence of heightened short-selling activity is associated with about 1.16% lower performance. The interaction of short-selling with news is also negative and statistically significant. It suggests that a one tercile increase in short-selling results in -1.204% lower gains.[2]

Next, we analyze the relation between retail trade gains and macro news. This table reports results from security-day-trade panel regressions of net trade gain in percent of market securities (ETFs and Index Funds) on macro announcement dummy indicators and other control variables. Following Ai and Bansal (2018), we focus on the five most important macroeconomic announcements (*MACRO_TOP5*): FOMC, Nonfarm Payroll (NFP), Producer Price Index (PPI), the advance estimate for GDP (GDP), and the ISM manufacturing index (ISM). *MACRO_BMO3* (*MACRO_DMH2*) is a dummy indicator for the three macro announcements that occur before (after) the market open.

[Table 10]

Table 10 reports the findings. Overall, the relation between market securities and macro news is positive and in some cases marginally significant, where the magnitude is about 0.50-0.70%. This is in contrast to our equity findings. One important reason is that information asymmetry is low for market securities. Consequently, retail investors do not lose to other market participants. The positive return can be related to the positive premium documented on market days.

3.6 Learning

One potential explanation for the fact that retail trade on news days quickly moves in the same direction as the news is overconfidence in their ability to process the news. One related question is, do retail investors who lose on news days learn from their mistakes? Overall, we find that retail investors do not learn from past losses and continue to lose on news days relative to non-news days.

To run these tests, we construct variables that capture past losses on news days relative to non-news days. More specifically, for each account and year t, we calculate the average difference between net trade gain on news days and non-news days. We then create an indicator variable,

[2]In Table IA.4 we repeat the analysis conducted in Table 9 for call and put options. Overall, the negative trade performance is concentrated in the call options, which comprise 70.75% of the options sample (=199,618 /282,157). However, both types of options contrast seem to lose when short-selling activity is high, where an increase of one tercile ranking of short-selling activity results in -1.234% (-1.880%) lower trade performance for call (put) options.

RLY_{t-1}, that is equal to one if the average difference is negative during year t-1. To be included in the tests, we require each account to have trades on at least 5 news days in year t-1.

[Table 11]

Table 11 reports the results. We run stock-day-trade panel regressions of net trade gain in percent in year t on a news dummy indicator ($NEWS$), the indicator of losses on news days relative to non-news days in year t-1 (RLY_{t-1}), its interaction with news ($NEWS\ x\ RLY_{t-1}$), and other control variables. Columns 1–3 focus on account year 2. This includes accounts that exist for at least two years in our sample, where we limit the analysis to year 2. $NEWS\ x\ RLY_{t-1}$, is the additional effect of trading on news days in year 2, conditioning on losses on news days in account year 1. Columns 4–6 include accounts that exist for at least two years in our sample, where we limit the analysis to year 2 or year 3. In this case, $NEWS\ x\ RLY_{t-1}$, is the additional effect of trading on news days in year t, conditioning on losses on news days in account year t-1, where t stands for year 2 or year 3. Across all specifications, the interaction variable is negative and statistically significant, where the relative losses range from -0.159% to -0.205% depending on the specification used. Importantly, the results suggest that retail investors who faced losses in previous years continue to lose on news days, where the magnitude of the losses is significant.

3.7 Other Tests and Robustness

Trading against informed investors - intraday evidence:

We revisit the analysis conducted in Table 7 where we explore the relation between short-selling intensity (a proxy for informed trading) and retail net trade gain in percent at the intraday level in a window of three hours from the release of public news. The analysis is based on a sub-sample of stock trades for which we have intraday timestamps. Given that the short-selling data captures mainly trading during regular market hours, we focus on news that occurs during market hours. Then for each stock and day, we keep the first time the news became available on RavenPack and assign its half-hour time interval (denoted as time 0). For example, for a news event that occurs at 11:10 am, we assign the 11:00-11:30 half-hour interval (denoted as "HH0"). We focus on short-selling intensity during the first half-hour after the news became public (HH1). We rank the normalized HH1 short-selling measures into terciles based on the pooled sample. Following

Panel B of Table 3, we keep retail trades up to three hours from the news event (HH1-HH6). In addition, we rank retail trades into terciles based on their duration (*ShortDuration_TER_HH16*), where a higher rank means a shorter trade duration. We include account ID and interval (HH0) fixed effects.

[Table 12]

Table 12 reports the findings. Across all specifications, heightened short-selling activity is associated with a lower trade performance between -0.208% - -0.254%. Trades with shorter duration are also associated with lower performance of about -0.140%, but it is marginally significant. Interestingly, the interaction between short-selling activity and trade duration is both statistically and economically significant, which suggests that trading aggressively against better-informed results results in losses.

Are retail investors contrarians?

Next, there is ample evidence that retail investors act as contrarians in general and around earnings days (Kaniel, Saar, and Titman, 2008; Kaniel, Liu, Saar, and Titman, 2012). In this type of analysis, retail order imbalance is regressed on contemporaneous and past returns, where negative coefficient estimates are an indication of a contrarian behavior. Interestingly, using account-level data, Barrot, Kaniel, and Sraer (2016) shows that this contrarian behavior may not translate into trade gains. Given this evidence, we are interested in exploring the behavior of retail investors in our sample in general and on news days. To this end, we follow Barrot et al. (2016) and regress daily retail order imbalance on contemporaneous and past returns, controlling for other stock characteristics, date fixed effects, and specifications with and without firm fixed effects.

Table IA.5 reports the results. We split the sample between news days and non-news days. Regardless of the specification and sample used, we find a stark difference in the relation between retail order imbalance and day t returns on news days and non-news days. When firm fixed effects are included, we even find a positive coefficient estimate, which suggests that retail investors trade in the same direction as the news. This is consistent with the findings of Table 5, where XX% of the observations are in the sample of long positions and positive returns.

Retail order imbalance and return predictability:

Another aspect of retail order imbalance is its ability to predict subsequent returns Boehmer, Jones, Zhang, and Zhang (2021). While evidence indicates that retail order imbalance can positively predict returns, other papers suggest of overreaction and subsequent reversals Barber et al. (2024). Thus, it is interesting to explore the properties of our sample, in particular on news days. Table IA.6 reports the findings. As in Table IA.5, we follow Barrot et al. (2016) and include date fixed effects and specifications with and without firm fixed effects. Similar to Table IA.5, we find a stark difference between news days and non-news days. Specifically, we find that retail order imbalance on non-news days is associated with subsequent reversals up to 5 trading days. In contrast, retail order imbalance on new days exhibits a positive relation, which is even significant depending on the specification used.

The fact that there is no reversal on news days and even return continuation is in contrast to the negative trade performance we exhibit on news days. This finding is consistent with Barrot et al. (2016), who argue that retail investors are not able to reap the rewards. In our case, retail investors close their position on the same day, which suggests that they do not benefit from the potential return continuation.

Account Heterogeneity:

Next, we explore the heterogeneity of our main finding based on account and stock characteristics. We rank all 5,182 accounts into terciles based on the total number of trades, the percentage of stock trades (of stocks and options trades), and holding period (duration). We then construct indicator variables that receive a value of one if the selected account characteristics are ranked in the top tercile across all accounts. In a similar manner, each day, we cross-sectionally rank all stocks in our sample into terciles based on stock market capitalization, stock turnover, and the previous month's stock returns and construct similar top tercile indicators.

We then extend the analysis conducted in Table 4 by including these indicators as controls and exploring their interaction with *NEWS*. Table IA.7 reports the results. Panel A indicates that controlling for top account characteristics does not alter our findings. For comparison, the coefficient estimate of Specification 4 of Table 4 is -0.123%, where the coefficient estimates across the six specifications range between -0.113% to -0.126%.

Next, in Panel B , we explore the tercile indicators' interactions with news. Interestingly, accounts with more trades seem to lose less on news days, which is consistent with experience. Next, the holding period reflects trading style, accounts that trade more aggressively (quicker) seem to lose more on news days. Next, retail investors seem to lose less in large stocks. This is consistent with the fact that the information gaps across investors are larger for smaller stocks, which makes it easier for more sophisticated investors to have an advantage.

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Table 1: Summary statistics

This table reports summary statistics conditioning on news events. Panel A (B) reports statistics at the stock-day (stock-day-trade) level. We split the sample into news and non-news days. For each subsample, we report the averages of key variables of interest, together with their standard errors (SE), and cross-sample differences (Diff). The sample period is from January 2020 to December 2022. Standard errors are double clustered by firm and date and reported in parentheses below the coefficient estimates. Statistical significance at the 10%, 5%, and 1% level is indicated with *, **, and ***, respectively.

Panel A: Stock Level Statistics

	News Days	SE	Other Days	SE	Diff	SE
Num Trades	11.028	0.594	6.201	0.230	4.827***	0.506
Ret (%)	4.286	0.292	2.473	0.125	1.813***	0.257
AbsRet (%)	10.326	0.406	6.729	0.125	3.597***	0.357
Turnover	0.316	0.025	0.231	0.014	0.085***	0.025
Effective Spread (%)	0.276	0.014	0.346	0.010	-0.07***	0.011
Kyle Lambda (10^{-6})	10.511	0.647	12.243	0.440	-1.732***	0.478
MktRet (%)	0.060	0.060	0.088	0.048	-0.028	0.024
AbsMktRet (%)	1.087	0.045	0.990	0.034	0.101***	0.020
Obs	25,035		151,744		176,779	
% Obs	14.16%					

Panel B: Trade Level Statistics

	News Days	SE	Other Days	SE	Diff	SE
Net Trade Gain Bps	0.766	2.944	13.808***	3.544	-13.042***	3.992
Net Trade Gain Bps - Exc. PreSignUp	-8.256**	3.534	1.121	3.085	-9.377**	4.229
Duration in Days	1.188***	0.084	2.069***	0.081	-0.881***	0.093
Duration in Minutes (SubSample)	25.824***	0.473	31.927***	0.470	-6.103***	0.548
Obs	362,212 [24.7%]		1,104,091		1,466,303	
Obs Exc. PreSignUp	176,711 [24.2%]		554,190		730,901	
Obs with timestamps	141,433 [25.7%]		408,876		550,309	

Table 2: Retail trading and attention triggers

This table reports results from stock-day panel regressions of the daily number of trades (aggregated across all accounts) on news dummy indicators and other control variables. The sample period is from January 2020 to December 2022. We include firm and date fixed effects. Standard errors are double clustered by firm and date and reported in parentheses below the coefficient estimates. Statistical significance at the 10%, 5%, and 1% level is indicated with *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
NEWS	4.827***	6.805***	2.316***	2.335***			2.386***	
	(0.51)	(0.33)	(0.26)	(0.26)			(0.26)	
AMC_NEWS					0.687*	0.542		0.545
					(0.36)	(0.36)		(0.36)
BMO_NEWS					1.730***	1.665***		1.672***
					(0.26)	(0.26)		(0.26)
DMH_NEWS					2.712***	2.693***		2.854***
					(0.48)	(0.48)		(0.48)
EDAY						0.427		0.332
						(0.37)		(0.38)
AbsRet			42.612***	41.059***	40.888***	40.855***	41.821***	41.625***
			(3.47)	(3.59)	(3.59)	(3.60)	(3.66)	(3.67)
AbnVolRatio			36.572***	37.253***	37.249***	37.257***	37.182***	37.180***
			(1.23)	(1.25)	(1.25)	(1.25)	(1.26)	(1.26)
ES			-5.741***	-5.154***	-5.174***	-5.177***	-5.018***	-5.044***
			(0.95)	(0.96)	(0.97)	(0.97)	(0.95)	(0.96)
AccRet t-26 t-5				0.007*	0.007*	0.007*	0.009**	0.009**
				(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
AveTurnover t-26 t-5				0.944	0.945	0.944	0.842	0.841
				(0.81)	(0.81)	(0.81)	(0.77)	(0.77)
SDRet t-26 t-5				0.084***	0.083***	0.084***	0.096***	0.096***
				(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
LnAveSize t-26 t-5				0.021	0.023	0.022	-0.755**	-0.759**
				(0.30)	(0.30)	(0.30)	(0.33)	(0.33)
Amihud				-0.034**	-0.034**	-0.034**	-0.030*	-0.030*
				(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
InstHold				-1.571	-1.579	-1.580	-2.419	-2.433
				(1.63)	(1.63)	(1.63)	(1.64)	(1.64)
Firm FE	NO	YES	YES	YES	YES	YES	YES	YES
DATE FE	NO	NO	NO	NO	NO	YES	YES	YES
Firm & Date Cluster	YES	YES	YES	YES	YES	YES	YES	YES
Observations	176,339	176,064	176,064	171,507	171,507	171,507	171,507	171,507
R^2	0.005	0.098	0.323	0.331	0.331	0.331	0.336	0.336

Table 3: How quickly do retail investors respond to news?

This table explores the intensity of retail trading around news events. Panel A reports the trading intensity at a daily frequency. For each stock j and news day t, we construct a seven-day window from day t-3 to t+3. We report the percentage fraction of each day relative to the total trades in a given window, net of the firm's expected benchmark. The benchmark is calculated using all non-news trades of stock j and the day-of-the-week of the news day. Finally, to account for the possibility of stale news, we remove consecutive news days from the analysis. Panel B reports the intraday trading intensity around the time of the news release net of the firm's expected benchmark. Trade timestamps are available for a subset of 551,342 trades (out of 1,466,303 trades). For each day and news event category, we keep the first timestamp at which the news appeared on RavenPack and define it as time 0. We keep all trades in a window of three hours [h-3, h+3] and require at least one trade. We then calculate the percentage fraction of trades in each hour relative to the total number of trades in that window. Similar to Panel A, we construct a benchmark based on all stock trades on non-news days in similar windows around the same intraday time stamp adjusted for the day-of-the-week. Standard errors are double clustered by firm and date and reported in parentheses below the coefficient estimates. Statistical significance at the 10%, 5%, and 1% level is indicated with *, **, and ***, respectively.

Panel A: Daily windows

	t-3	t-2	t-1	t	t+1	t+2	t+3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	-7.144***	-7.511***	-8.095***	43.236***	-5.972***	-7.040***	-7.475***
	(0.22)	(0.19)	(0.22)	(1.11)	(0.22)	(0.21)	(0.22)
Firm Cluster	YES	YES	YES	YES	YES	YES	YES
Observations	19,905	19,905	19,905	19,905	19,905	19,905	19,905
R^2	-0.000	-0.000	0.000	0.000	0.000	-0.000	-0.000

Panel B: Hourly windows

	h-3	h-2	h-1	h+1	h+2	h+3
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	-1.277***	-1.690***	-0.912**	7.415***	11.226***	2.848***
	(0.42)	(0.38)	(0.42)	(0.67)	(0.88)	(0.75)
Firm Cluster	YES	YES	YES	YES	YES	YES
Observations	3,870	3,870	3,870	3,871	3,872	3,873
R^2	0.000	-0.000	0.000	-0.000	-0.000	0.000

Table 4: Trade performance and news days

This table reports results from stock-day-trade panel regressions of net trade gain in percent on news dummy indicators and other control variables. The sample period is from January 2020 to December 2022. We include firm and account ID fixed effects. Standard errors are double clustered by firm and date and reported in parentheses below the coefficient estimates. Statistical significance at the 10%, 5%, and 1% level is indicated with *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
NEWS	-0.130***	-0.134***	-0.119***	-0.123***	-0.121***			
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)			
AMC_NEWS						0.031	0.017	0.018
						(0.05)	(0.05)	(0.06)
BMO_NEWS						-0.093**	-0.078**	-0.077**
						(0.04)	(0.04)	(0.04)
DMH_NEWS						-0.131**	-0.134***	-0.134***
						(0.05)	(0.05)	(0.05)
EDAY								-0.005
								(0.06)
PreSignUp Indic		0.235***	0.200***	0.178***	0.405***	0.177***	0.405***	0.405***
		(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.04)	(0.04)
AbsRet			0.069*	-0.096**	-0.058	-0.093**	-0.055	-0.055
			(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
AbnVolRatio			-0.003	-0.012**	-0.008	-0.012**	-0.008	-0.008
			(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
ES			0.265***	0.156**	0.125**	0.158**	0.127**	0.127**
			(0.08)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
AccRet t-26 t-5				-0.001**	-0.001**	-0.001**	-0.001**	-0.001**
				(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
AveTurnover t-26 t-5				-0.030*	-0.019	-0.030*	-0.019	-0.019
				(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
SDRet t-26 t-5				0.000	0.002	0.000	0.002	0.002
				(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
LnAveSize t-26 t-5				-0.605***	-0.597***	-0.606***	-0.597***	-0.597***
				(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Amihud				-0.001*	-0.001	-0.001**	-0.001*	-0.001*
				(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
InstHold				0.250	0.347	0.248	0.345	0.345
				(0.24)	(0.24)	(0.24)	(0.24)	(0.24)
Firm FE	NO	NO	YES	YES	YES	YES	YES	YES
ID FE	NO	NO	NO	NO	YES	NO	YES	YES
Firm & Date Cluster	YES	YES	YES	YES	YES	YES	YES	YES
Observations	1,466,303	1,466,303	1,466,060	1,393,955	1,393,802	1,393,955	1,393,802	1,393,802
R^2	0.000	0.000	0.008	0.010	0.055	0.010	0.055	0.055

Table 5: Trade performance and news days – position type and daily returns

This table extends the analysis reported in Table 4 by conditioning on position type (long or short) and the sign of the daily returns. The sample period is from January 2020 to December 2022. We include firm and account ID fixed effects. Standard errors are double clustered by firm and date and reported in parentheses below the coefficient estimates. Statistical significance at the 10%, 5%, and 1% level is indicated with *, **, and ***, respectively.

	ALL	LONG	$L + RET > 0$	$L + RET < 0$	SHORT	$S + RET > 0$	$S + RET < 0$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
NEWS	-0.121***	-0.241***	-0.247***	-0.144	0.073	0.053	-0.075
	(0.04)	(0.06)	(0.07)	(0.10)	(0.07)	(0.09)	(0.06)
PreSignUp Indic	0.405***	0.571***	0.419***	1.018***	0.102**	0.138**	-0.072
	(0.04)	(0.06)	(0.05)	(0.13)	(0.05)	(0.06)	(0.07)
AbsRet	-0.058	0.750***	0.742***	-3.167***	-1.426***	-1.364***	5.842***
	(0.04)	(0.12)	(0.11)	(0.85)	(0.13)	(0.13)	(0.50)
AbnVolRatio	-0.008	0.016	0.009	0.189	-0.023*	-0.013	-0.096
	(0.01)	(0.01)	(0.01)	(0.20)	(0.01)	(0.01)	(0.16)
ES	0.125**	0.018	-0.015	0.119*	0.400***	0.500**	0.013
	(0.06)	(0.08)	(0.22)	(0.07)	(0.12)	(0.20)	(0.11)
Controls	YES	YES	YES	YES	YES	YES	YES
ID & Firm FE	YES	YES	YES	YES	YES	YES	YES
Firm & Date Cluster	YES	YES	YES	YES	YES	YES	YES
Observations	1,393,802	867,169	670,247	193,136	525,954	396,135	127,632
R^2	0.055	0.073	0.071	0.156	0.087	0.090	0.208

Table 6: Trade duration and news days

This table reports results from stock-day-trade panel regressions of trade holding period in minutes on news dummy indicators and other control variables. Trade timestamps are available for a subset of 551,342 trades (out of 1,466,303 trades). The sample period is from January 2020 to December 2022. We include firm and account ID fixed effects. Standard errors are double clustered by firm and date and reported in parentheses below the coefficient estimates. Statistical significance at the 10%, 5%, and 1% level is indicated with *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
NEWS	-6.103***	-6.136***	-6.517***	-6.726***	-3.952***			
	(0.55)	(0.54)	(0.70)	(0.72)	(0.43)			
AMC_NEWS						-2.949***	-0.744	0.063
						(0.77)	(0.57)	(0.56)
BMO_NEWS						-4.329***	-1.595***	-1.347***
						(0.68)	(0.43)	(0.44)
DMH_NEWS						-5.788***	-4.406***	-4.330***
						(0.79)	(0.55)	(0.55)
EDAY								-2.485***
								(0.62)
PreSignUp Indic		5.807***	4.470***	4.692***	-1.180***	4.668***	-1.193***	-1.206***
		(0.48)	(0.40)	(0.42)	(0.41)	(0.42)	(0.41)	(0.41)
AbsRet			-5.870***	-5.885***	-4.676***	-5.844***	-4.604***	-4.607***
			(0.86)	(0.74)	(0.54)	(0.73)	(0.54)	(0.54)
AbnVolRatio			-0.395***	-0.424***	-0.248***	-0.428***	-0.253***	-0.254***
			(0.08)	(0.08)	(0.05)	(0.07)	(0.05)	(0.05)
ES			3.304**	3.327**	1.358*	3.363**	1.493*	1.499*
			(1.52)	(1.60)	(0.80)	(1.63)	(0.84)	(0.84)
AccRet t-26 t-5				0.002	-0.001	0.003	-0.000	-0.001
				(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
AveTurnover t-26 t-5				-0.563	-0.182	-0.555	-0.184	-0.192
				(0.38)	(0.26)	(0.38)	(0.26)	(0.26)
SDRet t-26 t-5				-0.077***	-0.028	-0.079***	-0.028	-0.028
				(0.03)	(0.02)	(0.03)	(0.02)	(0.02)
LnAveSize t-26 t-5				1.042**	0.624**	1.014**	0.589**	0.601**
				(0.48)	(0.30)	(0.48)	(0.29)	(0.30)
Amihud				-0.009	-0.005*	-0.009	-0.006*	-0.006*
				(0.01)	(0.00)	(0.01)	(0.00)	(0.00)
InstHold				-3.498	0.397	-3.463	0.351	0.428
				(2.98)	(2.24)	(3.00)	(2.25)	(2.26)
Firm FE	NO	NO	YES	YES	YES	YES	YES	YES
ID FE	NO	NO	NO	NO	YES	NO	YES	YES
Firm & Date Cluster	YES	YES	YES	YES	YES	YES	YES	YES
Observations	550,309	550,309	549,932	521,190	521,122	521,190	521,122	521,122
R^2	0.002	0.004	0.056	0.058	0.248	0.058	0.248	0.249

Table 7: Trading against sophisticated investors

This table reports results from stock-day-trade panel regressions of trade net trade gain in percent on a news dummy indicator, short-selling intensity (as a proxy for informed trading), their interaction, and other control variables. Short-selling volume data is obtained from FINRA. For each firm, we aggregate the short-selling volume at the daily level and normalize it by the number of outstanding shares. We then rank the normalized short-selling measure into terciles (*SS_TER*), where tercile 3 (1) captures high (low) informed trading activity. The number of regression observations is based on the intersection of both data sets. The sample period is from January 2020 to December 2022. We include firm and account ID fixed effects. Standard errors are double clustered by firm and date and reported in parentheses below the coefficient estimates. Statistical significance at the 10%, 5%, and 1% level is indicated with *, **, and ***, respectively.

	ALL			LONG			SHORT		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
NEWS	-0.149***	-0.135***	0.060	-0.245***	-0.225***	0.138	0.036	0.041	-0.048
	(0.04)	(0.04)	(0.08)	(0.07)	(0.07)	(0.12)	(0.03)	(0.03)	(0.07)
SS_TER		-0.086**	-0.064		-0.128**	-0.090		-0.033	-0.044
		(0.04)	(0.04)		(0.05)	(0.06)		(0.03)	(0.04)
NEWS x SS_TER			-0.100**			-0.190***			0.044
			(0.04)			(0.07)			(0.04)
AbsRet	1.024***	1.125***	1.136***	3.225***	3.393***	3.413***	-1.925***	-1.894***	-1.899***
	(0.36)	(0.39)	(0.39)	(0.44)	(0.46)	(0.46)	(0.49)	(0.51)	(0.51)
AbnVolRatio	0.293	0.615	0.631	-3.648***	-3.142***	-3.111***	4.801***	4.921***	4.915***
	(0.64)	(0.65)	(0.65)	(0.94)	(0.96)	(0.96)	(0.73)	(0.75)	(0.75)
ES	0.155**	0.146**	0.148**	0.039	0.026	0.029	0.411***	0.407***	0.406***
	(0.07)	(0.07)	(0.07)	(0.10)	(0.10)	(0.10)	(0.12)	(0.12)	(0.12)
AccRet t-26 t-5	-0.001*	-0.001*	-0.001*	-0.003***	-0.003***	-0.003***	0.001	0.001	0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
AveTurnover t-26 t-5	-0.029	-0.018	-0.019	0.022	0.036	0.034	0.066	0.078	0.079
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.27)	(0.28)	(0.28)
SDRet t-26 t-5	-0.003	-0.002	-0.002	-0.003	-0.002	-0.002	0.003	0.003	0.004
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
LnAveSize t-26 t-5	-1.295***	-1.306***	-1.305***	-1.703***	-1.719***	-1.718***	-0.128**	-0.132**	-0.133**
	(0.08)	(0.08)	(0.08)	(0.10)	(0.10)	(0.10)	(0.05)	(0.05)	(0.05)
Amihud	-0.001	-0.002	-0.002	-0.004	-0.004	-0.004	0.003	0.003	0.003
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
InstHold	-0.443	-0.428	-0.427	-0.690	-0.666	-0.664	-0.125	-0.121	-0.121
	(0.36)	(0.36)	(0.35)	(0.46)	(0.46)	(0.46)	(0.21)	(0.21)	(0.21)
Constant	10.965***	11.212***	11.154***	13.917***	14.281***	14.184***	1.521***	1.614***	1.646***
	(0.66)	(0.68)	(0.67)	(0.85)	(0.87)	(0.86)	(0.49)	(0.51)	(0.51)
ID & Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm & Date Cluster	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	491,408	491,408	491,408	325,099	325,099	325,099	165,477	165,477	165,477
R^2	0.118	0.118	0.118	0.135	0.135	0.135	0.190	0.190	0.190

Table 8: Net Trade Gain and Social Media Attention

This table reports results from stock-day-trade panel regressions of net trade gain in percent on social media attention and its interaction with short-selling intensity. We measure social media attention following Cookson et al. (2024b) as the daily abnormal number of user messages on social media of firm j on day t. Abnormal social media activity is calculated as day t's number of user messages relative to its 3-month rolling average. We rank the measure into terciles (*SM_TER*), where tercile 3 (1) captures high (low) social media attention. Columns 1–2 are based on the social media sample. Columns 3–8 are based on the intersection of the social media and FINRA's SS samples. Social media data are obtained from Cookson et al. (2024b) and are available until December 2021. We include firm and account ID fixed effects. Standard errors are double clustered by firm and date and reported in parentheses below the coefficient estimates. Statistical significance at the 10%, 5%, and 1% level is indicated with *, **, and ***, respectively.

	SM SMP		SM & SS SMP					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
NEWS	-0.175***	-0.141***	-0.285***	-0.249***	-0.236***	0.164	-0.239***	0.171
	(0.05)	(0.05)	(0.07)	(0.07)	(0.07)	(0.14)	(0.07)	(0.14)
SM_TER		-0.060		-0.106**	-0.059		0.038	-0.001
		(0.06)		(0.04)	(0.05)		(0.10)	(0.11)
SS_TER					-0.183**	-0.165**	-0.073	-0.065
					(0.07)	(0.07)	(0.14)	(0.14)
NEWS x SS_TER						-0.213***		-0.208***
						(0.07)		(0.07)
SM_TER x SS_TER							-0.052	-0.033
							(0.05)	(0.05)
AbsRet	-0.069	-0.056	2.340***	2.558***	2.861***	2.832***	2.891***	2.916***
	(0.05)	(0.06)	(0.46)	(0.49)	(0.54)	(0.53)	(0.55)	(0.56)
AbnVolRatio	-0.008	-0.008	0.024	0.046	0.073	0.066	0.079	0.077
	(0.01)	(0.01)	(0.24)	(0.23)	(0.22)	(0.22)	(0.22)	(0.22)
ES	0.102*	0.100*	0.059	0.055	0.044	0.048	0.044	0.048
	(0.06)	(0.06)	(0.07)	(0.07)	(0.07)	(0.08)	(0.08)	(0.08)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
ID & Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Firm & Date Cluster	YES	YES	YES	YES	YES	YES	YES	YES
Observations	838,855	822,458	245,568	245,568	245,568	245,568	245,568	245,568
R^2	0.065	0.065	0.134	0.134	0.134	0.135	0.134	0.135

Table 9: Stock Option Trades and News Days

This table explores the profitability of stock option trades (net trade gain) on news days. Panel A repeats the analysis conducted in Table 4, Panel B repeats the analysis conducted in Table 5, and Panel C repeats the analysis conducted in Table 7. The sample period is from January 2020 to December 2022. The top 10 heavily traded stock options are excluded. We include firm and account ID fixed effects. Standard errors are double clustered by firm and date and reported in parentheses below the coefficient estimates. Statistical significance at the 10%, 5%, and 1% level is indicated with *, **, and ***, respectively.

Panel A: Trade Performance - Base

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
NEWS	-2.225***	-2.224***	-1.843***	-2.307***	-2.030***			
	(0.50)	(0.50)	(0.48)	(0.55)	(0.52)			
AMC_NEWS						-2.353***	-2.794***	-2.405**
						(0.81)	(0.81)	(0.97)
BMO_NEWS						-0.965*	-0.629	-0.450
						(0.59)	(0.57)	(0.59)
DMH_NEWS						-2.043**	-1.840**	-1.748**
						(0.80)	(0.78)	(0.78)
EDAY								-1.321
								(1.34)
PreSignUp Indic		0.145	0.312	0.257	0.394	0.376	2.695***	2.684***
		(0.38)	(0.36)	(0.36)	(0.37)	(0.37)	(0.57)	(0.57)
AbsRet				13.640**	10.336*	10.467*	12.607*	12.668*
				(5.51)	(6.06)	(6.14)	(6.70)	(6.75)
AbnVolRatio				4.749	-12.310	-7.897	17.365	19.256
				(22.11)	(19.58)	(19.82)	(19.83)	(19.76)
ES				-4.486	-5.895	-5.892	-7.017*	-7.003*
				(4.42)	(4.04)	(4.05)	(3.84)	(3.84)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	NO	NO	YES	YES	YES	YES	YES	YES
ID FE	NO	NO	NO	NO	NO	YES	YES	YES
Firm & Date Cluster	YES	YES	YES	YES	YES	YES	YES	YES
Observations	286,334	286,334	285,906	285,906	282,536	282,536	282,425	282,425
R^2	0.000	0.000	0.010	0.011	0.012	0.012	0.041	0.041

Panel B: Trade Performance - Position Type and Daily Returns

	ALL	LONG	$L + RET > 0$	$L + RET < 0$	SHORT	$S + RET > 0$	$S + RET < 0$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
NEWS	-2.030***	-2.338***	-2.007**	-2.278**	1.145	-1.149	4.262**
	(0.55)	(0.68)	(0.95)	(0.91)	(1.81)	(2.80)	(2.11)
PreSignUp Indic	0.394	3.320***	3.566***	2.132**	1.534	0.185	4.596*
	(0.83)	(0.65)	(0.81)	(0.98)	(2.16)	(3.32)	(2.61)
AbsRet	10.336*	18.552*	16.435	-3.964	-24.794	-27.445	9.132
	(6.15)	(10.62)	(13.84)	(8.41)	(17.76)	(25.71)	(17.63)
AbnVolRatio	-12.310	33.887	28.918	20.173	28.793	78.099	-66.297
	(20.85)	(30.97)	(42.13)	(27.47)	(53.24)	(79.27)	(58.45)
ES	-5.895	-3.752**	-4.317	-3.286**	-13.196	13.228	-17.060
	(4.02)	(1.65)	(5.87)	(1.66)	(10.63)	(15.40)	(12.80)
Controls	YES	YES	YES	YES	YES	YES	YES
ID & Firm FE	YES	YES	YES	YES	YES	YES	YES
Firm & Date Cluster	YES	YES	YES	YES	YES	YES	YES
Observations	282,536	226,930	131,707	93,941	54,904	26,404	27,789
R^2	0.012	0.044	0.060	0.067	0.085	0.111	0.110

Panel C: Trade Performance and Sophisticated Investors

	ALL			LONG			SHORT		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
NEWS	-1.655***	-1.589***	0.910	-2.381***	-2.244***	2.310	1.375	1.072	-3.105
	(0.49)	(0.48)	(1.20)	(0.71)	(0.69)	(1.47)	(1.92)	(1.93)	(4.81)
SS_TER		-1.163***	-0.977**		-2.442***	-2.089***		5.450***	5.190***
		(0.42)	(0.42)		(0.61)	(0.62)		(1.36)	(1.39)
NEWS x SS_TER			-1.204**			-2.183***			2.073
			(0.57)			(0.72)			(2.00)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
ID & Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm & Date Cluster	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	255,570	255,570	255,570	204,903	204,903	204,903	50,087	50,087	50,087
R^2	0.043	0.043	0.043	0.045	0.045	0.046	0.086	0.086	0.086

Table 10: Market Securities Trade Performance on Macro Announcement Days

This table reports results from security-day-trade panel regressions of net trade gain in percent of market securities (ETFs and Index Funds) on macro announcement dummy indicators and other control variables. Following Ai and Bansal (2018), we focus on the five most important macroeconomic announcements (*MACRO_TOP5*): FOMC, Nonfarm Payroll (NFP), Producer Price Index (PPI), the advance estimate for GDP (GDP), and the ISM manufacturing index (ISM). *MACRO_BMO3* (*MACRO_DMH2*) is a dummy indicator for the three macro announcements that occur before (after) the market open. The sample period is from January 2020 to December 2022. Standard errors are double clustered by firm and date and reported in parentheses below the coefficient estimates. Statistical significance at the 10%, 5%, and 1% level is indicated with *, **, and ***, respectively.

	ALL		BMO		DMH	
	(1)	(2)	(3)	(4)	(5)	(6)
MACRO_TOP5	0.715*	0.697*				
	(0.39)	(0.40)				
MACRO_BMO3			0.522	0.531		
			(0.44)	(0.45)		
MACRO_DMH2					0.752	0.733
					(0.65)	(0.67)
AbsMKTRET	0.304*	0.247	0.309*	0.251	0.332*	0.274
	(0.18)	(0.18)	(0.18)	(0.18)	(0.18)	(0.19)
VIX	0.008	0.017	0.008	0.017	0.005	0.014
	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)	(0.04)
PreSignUp Indic	0.712***	0.748**	0.710***	0.747**	0.708***	0.745**
	(0.19)	(0.33)	(0.19)	(0.33)	(0.19)	(0.33)
ID FE	NO	YES	NO	YES	NO	YES
Date Cluster	YES	YES	YES	YES	YES	YES
Observations	343,466	343,168	343,466	343,168	343,466	343,168
R^2	0.000	0.015	0.000	0.015	0.000	0.015

Table 11: Is There Learning from Past Losses on News Days?

This table reports results from stock-day-trade panel regressions of net trade gain in percent in year t on a news dummy indicator (*NEWS*), an account indicator of losses on news days relative to non-news days in year t-1 (RLY_{t-1}), its interaction with news (*NEWS x* RLY_{t-1}), and other control variables. In particular, for each account and year t, we calculate the average difference between net trade gain on news days and non-news days. We then create an indicator variable that is equal to one if the average difference is negative during year t-1. To be included in the tests, we require each account to have trades on at least 5 news days in year t-1. Columns 1–3 focus on account year 2. This includes accounts that exist for at least two years in our sample, where we limit the analysis to year 2. *NEWS x* RLY_{t-1}, is the additional effect of trading on news days in year 2, conditioning on losses on news days in account year 1. Columns 4–6 includes accounts that exist for at least two years in our sample, where we limit the analysis to year 2 or year 3. In this case, *NEWS x* RLY_{t-1}, is the additional effect of trading on news days in year t, conditioning on losses on news days in account year t-1, where t stands for year 2 or year 3. The sample period is from January 2020 to December 2022. We include firm and account ID fixed effects. Standard errors are double clustered by firm and date and reported in parentheses below the coefficient estimates. Statistical significance at the 10%, 5%, and 1% level is indicated with *, **, and ***, respectively.

	Account Year 2			Account Years 2 or 3		
	(1)	(2)	(3)	(4)	(5)	(6)
NEWS	0.014	0.025	-0.028	0.026	0.043	0.014
	(0.07)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
NEWS x RLY_{t-1}	-0.205***	-0.189***	-0.159***	-0.203***	-0.193***	-0.181***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Controls	NO	YES	YES	NO	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
ID FE	NO	NO	YES	NO	NO	YES
Firm & Date Cluster	YES	YES	YES	YES	YES	YES
Observations	464,587	440,590	440,590	553,151	522,532	522,532
R^2	0.013	0.015	0.042	0.011	0.013	0.038

Table 12: Trading against sophisticated investors - Intraday Evidence

This table revisits the relation between short-selling intensity (a proxy for informed trading) and retail net trade gain in percent at the intraday level in a window of three hours from the release of public news. The analysis is based on a sub-sample of stock trades with intraday timestamps. Given that the short-selling data captures mainly trading during regular market hours, we focus on news that occurs during market hours. For each stock and day, we keep the first time the news became available on RavenPack and assign its half-hour time interval (denoted as time 0). For example, for a news event that occurs at 11:10 am, we assign the 11:00-11:30 half-hour interval (denoted as "HH0"). We focus on short-selling intensity during the first half-hour after the news became public (HH1). We rank the normalized HH1 short-selling measures into terciles based on the pooled sample. Following Panel B of Table 3, we keep retail trades up to three hours from the news event (HH1-HH6). In addition, we rank retail trades into terciles based on their duration (*ShortDuration_TER_HH16*), where a higher rank means a shorter trade duration. We include account ID and interval (HH0) fixed effects. Standard errors are double clustered by firm and date and reported in parentheses below the coefficient estimates. Statistical significance at the 10%, 5%, and 1% level is indicated with *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
SS_TER_HH1	-0.216***	-0.208***	0.294*	-0.253***	-0.254***	0.231
	(0.08)	(0.08)	(0.15)	(0.09)	(0.09)	(0.17)
ShortDuration_TER_HH16		-0.090	0.404***		-0.140*	0.342**
		(0.08)	(0.14)		(0.08)	(0.15)
SS HH1 X ShortDuration HH16			-0.250***			-0.239***
			(0.08)			(0.08)
ID FE	YES	YES	YES	YES	YES	YES
Interval FE	NO	NO	NO	YES	YES	YES
Firm and Date Cluster	YES	YES	YES	YES	YES	YES
Observations	35,829	35,829	35,829	35,829	35,829	35,829
R^2	0.066	0.066	0.066	0.066	0.066	0.067

Internet Appendix

Table IA.1: How quickly do retail investors respond to *earnings* news?

This table repeats the analysis conducted in Table 3 for earnings days. As in Table 3, in Panel A, we explore the intensity of trading around earnings news at a daily frequency. In panel B, we explore the intraday trading intensity around the time of earnings release during market hours. Standard errors are double clustered by firm and date and reported in parentheses below the coefficient estimates. Statistical significance at the 10%, 5%, and 1% level is indicated with *, **, and ***, respectively.

Panel A: Daily windows

	t-3	t-2	t-1	t	t+1	t+2	t+3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	-11.190***	-11.307***	-9.191***	58.437***	-7.118***	-9.362***	-10.268***
	(0.20)	(0.20)	(0.31)	(0.65)	(0.31)	(0.22)	(0.20)
Firm Cluster	YES	YES	YES	YES	YES	YES	YES
Observations	4,285	4,285	4,285	4,285	4,285	4,285	4,285
R^2	-0.000	0.000	-0.000	-0.000	0.000	-0.000	0.000

Panel B: Hourly windows

	h-3	h-2	h-1	h+1	h+2	h+3
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	-0.785	-2.329	-1.665*	5.496***	11.108***	17.148***
	(0.96)	(1.67)	(0.85)	(1.42)	(2.43)	(2.98)
Firm Cluster	YES	YES	YES	YES	YES	YES
Observations	390	390	390	390	390	390
R^2	-0.000	0.000	-0.000	-0.000	-0.000	0.000

Table IA.2: The Economic Significance of news Relative to Other Attention Drivers: Tables 2, 4, 6, and 7

To facilitate a clearer comparison of the economic significance of news relative to other attention drivers, this table extends the analyses presented in Tables 2, 4, 6, and 7 by Z-scoring (a mean of zero and a standard deviation of one, denoted with Z) day-t's return and trading volume. The sample period is from January 2020 to December 2022. We include firm and account ID fixed effects. Standard errors are double clustered by firm and date and reported in parentheses below the coefficient estimates. Statistical significance at the 10%, 5%, and 1% level is indicated with *, **, and ***, respectively.

Panel A: Table 2 - Daily Number of Trades

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
NEWS	4.827***	6.805***	2.316***	2.335***			2.386***	
	(0.51)	(0.33)	(0.26)	(0.26)			(0.26)	
AMC_NEWS					0.687*	0.542		0.545
					(0.36)	(0.36)		(0.36)
BMO_NEWS					1.730***	1.665***		1.672***
					(0.26)	(0.26)		(0.26)
DMH_NEWS					2.712***	2.693***		2.854***
					(0.48)	(0.48)		(0.48)
EDAY						0.427		0.332
						(0.37)		(0.38)
AbsRet(Z)			6.624***	6.382***	6.356***	6.351***	6.501***	6.470***
			(0.54)	(0.56)	(0.56)	(0.56)	(0.57)	(0.57)
AbnVolRatio(Z)			9.648***	9.828***	9.827***	9.829***	9.809***	9.809***
			(0.33)	(0.33)	(0.33)	(0.33)	(0.33)	(0.33)
ES(Z)			-2.569***	-2.307***	-2.316***	-2.317***	-2.246***	-2.257***
			(0.43)	(0.43)	(0.43)	(0.43)	(0.43)	(0.43)
Controls	NO	NO	NO	YES	YES	YES	YES	YES
Firm FE	NO	YES	YES	YES	YES	YES	YES	YES
DATE FE	NO	NO	NO	NO	NO	YES	YES	YES
Firm & Date Cluster	YES	YES	YES	YES	YES	YES	YES	YES
Observations	176,339	176,064	176,064	171,507	171,507	171,507	171,507	171,507
R^2	0.005	0.098	0.323	0.331	0.331	0.331	0.336	0.336

Panel B: Table 4 - Net Trade Gain

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
NEWS	-0.130***	-0.134***	-0.119***	-0.123***	-0.121***			
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)			
AMC_NEWS						0.031	0.017	0.018
						(0.05)	(0.05)	(0.06)
BMO_NEWS						-0.093**	-0.078**	-0.077**
						(0.04)	(0.04)	(0.04)
DMH_NEWS						-0.131**	-0.134***	-0.134***
						(0.05)	(0.05)	(0.05)
EDAY								-0.005
								(0.06)
AbsRet(Z)			0.056*	-0.078**	-0.047	-0.075**	-0.045	-0.045
			(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
AbnVolRatio(Z)			-0.012	-0.045**	-0.030	-0.045**	-0.030	-0.030
			(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
ES(Z)			0.118***	0.070**	0.056**	0.071**	0.057**	0.057**
			(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	NO	NO	YES	YES	YES	YES	YES	YES
ID FE	NO	NO	NO	NO	YES	NO	YES	YES
Firm & Date Cluster	YES	YES	YES	YES	YES	YES	YES	YES
Observations	1,466,303	1,466,303	1,466,060	1,393,955	1,393,802	1,393,955	1,393,802	1,393,802
R^2	0.000	0.000	0.008	0.010	0.055	0.010	0.055	0.055

Panel C: Table 6 - Trade Duration

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
NEWS	-6.103***	-6.136***	-6.517***	-6.726***	-3.952***			
	(0.55)	(0.54)	(0.70)	(0.72)	(0.43)			
AMC_NEWS						-2.949***	-0.744	0.063
						(0.77)	(0.57)	(0.56)
BMO_NEWS						-4.329***	-1.595***	-1.347***
						(0.68)	(0.43)	(0.44)
DMH_NEWS						-5.788***	-4.406***	-4.330***
						(0.79)	(0.55)	(0.55)
EDAY								-2.485***
								(0.62)
AbsRet(Z)			-4.967***	-4.979***	-3.956***	-4.945***	-3.895***	-3.898***
			(0.72)	(0.62)	(0.46)	(0.62)	(0.46)	(0.46)
AbnVolRatio(Z)			-1.618***	-1.737***	-1.016***	-1.755***	-1.035***	-1.041***
			(0.31)	(0.32)	(0.22)	(0.31)	(0.22)	(0.22)
ES(Z)			1.336**	1.345**	0.549*	1.360**	0.604*	0.606*
			(0.62)	(0.65)	(0.32)	(0.66)	(0.34)	(0.34)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	NO	NO	YES	YES	YES	YES	YES	YES
ID FE	NO	NO	NO	NO	YES	NO	YES	YES
Firm & Date Cluster	YES	YES	YES	YES	YES	YES	YES	YES
Observations	550,309	550,309	549,932	521,190	521,122	521,190	521,122	521,122
R^2	0.002	0.004	0.056	0.058	0.248	0.058	0.248	0.249

Panel D: Table 7 - Trading Against Informed

	ALL			LONG			SHORT		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
NEWS	-0.149***	-0.135***	0.060	-0.245***	-0.225***	0.138	0.036	0.041	-0.048
	(0.04)	(0.04)	(0.08)	(0.07)	(0.07)	(0.12)	(0.03)	(0.03)	(0.07)
SS_TER		-0.086**	-0.064		-0.128**	-0.090		-0.033	-0.044
		(0.04)	(0.04)		(0.05)	(0.06)		(0.03)	(0.04)
NEWS x SS_TER			-0.100**			-0.190***			0.044
			(0.04)			(0.07)			(0.04)
AbsRet(Z)	0.127***	0.139***	0.141***	0.399***	0.420***	0.422***	-0.238***	-0.234***	-0.235***
	(0.04)	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
AbnVolRatio(Z)	0.016	0.034	0.034	-0.199***	-0.171***	-0.170***	0.262***	0.268***	0.268***
	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)
ES(Z)	0.060**	0.056**	0.057**	0.015	0.010	0.011	0.159***	0.157***	0.157***
	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
ID & Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm & Date Cluster	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	491,408	491,408	491,408	325,099	325,099	325,099	165,477	165,477	165,477
R^2	0.118	0.118	0.118	0.135	0.135	0.135	0.190	0.190	0.190

Table IA.3: Short Selling Data Validation

This table explores the relation between FINRA's short-selling data and subsequent stock returns. Columns 1–3 (4–6) use the ranked (continuous) short-selling measure. The sample period is from January 2020 to December 2022. We report specifications with date fixed effects. Standard errors are double clustered by firm and date and reported in parentheses below the coefficient estimates. Statistical significance at the 10%, 5%, and 1% level is indicated with *, **, and ***, respectively.

	CumRET1	CumRET10	CumRET20	CumRET1	CumRET10	CumRET20
	(1)	(2)	(3)	(4)	(5)	(6)
SS_TER	-0.167***	-0.397***	-0.781***			
	(0.04)	(0.15)	(0.24)			
SS				-17.669***	-42.216***	-63.573***
				(2.71)	(9.43)	(15.35)
RET	-0.895*	0.513	0.899	-0.848	0.629	1.019
	(0.53)	(1.36)	(1.83)	(0.53)	(1.36)	(1.83)
AbnVolRatio	-0.859	-9.171**	-3.253	0.555	-5.808	0.375
	(1.58)	(4.19)	(6.08)	(1.60)	(4.31)	(6.28)
ES	0.302***	-0.086	-0.167	0.282***	-0.136	-0.193
	(0.10)	(0.24)	(0.37)	(0.10)	(0.24)	(0.37)
AccRet t-26 t-5	-0.001	-0.001	-0.001	-0.001	-0.000	-0.001
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)
AveTurnover t-26 t-5	0.004	-0.818	-1.283	0.063	-0.686	-1.124
	(0.06)	(0.56)	(1.01)	(0.05)	(0.47)	(0.90)
SDRet t-26 t-5	-0.008	-0.065**	-0.107**	-0.005	-0.059**	-0.103**
	(0.01)	(0.03)	(0.04)	(0.01)	(0.03)	(0.04)
LnAveSize t-26 t-5	-0.077***	-0.164***	-0.287***	-0.086***	-0.185***	-0.297***
	(0.01)	(0.05)	(0.09)	(0.01)	(0.05)	(0.08)
Amihud	-0.001	-0.004	-0.016*	-0.001	-0.004	-0.016*
	(0.00)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)
InstHold	0.199**	1.355***	3.054***	0.183*	1.312***	3.009***
	(0.10)	(0.45)	(0.78)	(0.10)	(0.43)	(0.77)
Date FE	YES	YES	YES	YES	YES	YES
Firm & Date Cluster	YES	YES	YES	YES	YES	YES
Observations	148,956	141,991	134,454	148,956	141,991	134,454
R^2	0.126	0.181	0.198	0.127	0.181	0.199

Table IA.4: Stock Option Trades - Call and Put Breakdown

This table repeats the main analysis conducted in Table 9 for calls and puts options. Panel A (B) repeats the analysis conducted in Panel B of Table 9 for calls (puts). Panel C (D) repeats the analysis conducted in Panel C of Table 9 for calls (puts). The sample period is from January 2020 to December 2022. We include firm and account ID fixed effects. Standard errors are double clustered by firm and date and reported in parentheses below the coefficient estimates. Statistical significance at the 10%, 5%, and 1% level is indicated with *, **, and ***, respectively.

Panel A: Trade Performance - Type and Returns - Call Options

	ALL	LONG	$L+RET>0$	$L+RET<0$	SHORT	$S+RET>0$	$S+RET<0$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
NEWS	-2.140***	-3.231***	-3.124***	-2.295**	4.074	0.303	7.407**
	(0.66)	(0.85)	(1.12)	(1.05)	(2.68)	(4.40)	(3.20)
PreSignUp Indic	-0.284	1.098**	0.530	0.741	-1.434	-3.596	1.843
	(0.47)	(0.51)	(0.57)	(0.74)	(2.36)	(2.96)	(3.00)
AbsRet	24.535**	35.738*	35.211	-74.097***	-54.095	-62.035	57.334*
	(11.05)	(18.53)	(24.64)	(15.61)	(34.74)	(48.61)	(30.82)
AbnVolRatio	-23.162	30.337	11.900	115.252***	-51.846	12.591	-245.679**
	(29.69)	(47.47)	(63.98)	(40.12)	(106.11)	(137.52)	(119.71)
ES	0.177	-5.354	-6.777	-1.109	5.868	41.766*	1.048
	(2.39)	(3.70)	(7.52)	(6.40)	(5.81)	(23.04)	(4.15)
Controls	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES
ID FE	NO	NO	NO	NO	NO	NO	NO
Firm & Date Cluster	YES	YES	YES	YES	YES	YES	YES
Observations	199,618	168,961	107,953	60,066	30,257	15,995	13,830
R^2	0.016	0.030	0.037	0.041	0.051	0.069	0.072

Panel B: Trade Performance - Type and Returns - Put Options

	ALL	LONG	$L+RET>0$	$L+RET<0$	SHORT	$S+RET>0$	$S+RET<0$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
NEWS	-1.388	-0.611	1.182	-1.918	-2.810	-3.407	-0.568
	(0.93)	(1.40)	(2.07)	(1.76)	(2.51)	(4.06)	(2.97)
PreSignUp Indic	1.696**	-4.869***	-3.029**	-5.458***	16.644***	15.828***	16.860***
	(0.67)	(0.91)	(1.25)	(0.99)	(2.27)	(3.30)	(2.64)
AbsRet	-9.545***	-0.887	-10.542	66.607***	-12.185	3.718	-68.953**
	(2.85)	(5.34)	(7.86)	(13.41)	(9.20)	(11.14)	(33.13)
AbnVolRatio	-10.731	17.081	56.862	-76.081*	58.128	26.751	136.448
	(16.93)	(25.05)	(44.14)	(40.02)	(49.72)	(60.62)	(86.16)
ES	-11.614	-2.092	12.418	-4.352***	-26.881***	-9.216	-33.706***
	(7.36)	(2.62)	(8.31)	(1.61)	(7.51)	(11.98)	(8.87)
Controls	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES
ID FE	NO	NO	NO	NO	NO	NO	NO
Firm & Date Cluster	YES	YES	YES	YES	YES	YES	YES
Observations	82,539	57,670	23,541	33,698	24,482	10,236	13,861
R^2	0.019	0.043	0.059	0.046	0.060	0.090	0.076

Panel C: Trade Performance and Sophisticated Investors - Call Options

	ALL			LONG			SHORT		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
NEWS	-1.824***	-1.759***	0.776	-2.876***	-2.760***	1.069	4.056	3.803	0.566
	(0.58)	(0.58)	(1.25)	(0.78)	(0.78)	(1.46)	(3.05)	(3.05)	(7.62)
SS_TER		-1.354**	-1.158**		-2.443***	-2.136***		5.548***	5.343***
		(0.56)	(0.58)		(0.70)	(0.73)		(1.72)	(1.71)
NEWS x SS_TER			-1.234**			-1.858***			1.614
			(0.58)			(0.70)			(3.24)
AbsRet	68.326***	69.011***	69.491***	94.234***	95.327***	96.088***	-104.677***	-108.647***	-109.096***
	(10.20)	(10.26)	(10.24)	(14.86)	(14.98)	(14.93)	(37.17)	(37.40)	(37.45)
AbnVolRatio	-30.205	6.389	9.977	-17.866	48.137	53.327	91.578	-65.446	-71.637
	(39.31)	(41.97)	(42.32)	(55.41)	(58.39)	(58.95)	(157.35)	(162.22)	(164.17)
ES	1.535	1.309	1.313	-2.772	-3.695	-3.633	2.860	3.042	3.065
	(3.34)	(3.35)	(3.34)	(9.00)	(8.98)	(8.96)	(2.36)	(2.42)	(2.41)
Controls & Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
ID & Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm & Date Cluster	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	180,504	180,504	180,504	152,481	152,481	152,481	27,502	27,502	27,502
R^2	0.054	0.054	0.054	0.057	0.057	0.057	0.124	0.124	0.124

Panel D: Trade Performance and Sophisticated Investors - Put Options

	ALL			LONG			SHORT		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
NEWS	-1.015	-0.969	2.852	-0.678	-0.594	4.020	-2.719	-2.871	-0.098
	(0.99)	(0.98)	(1.98)	(1.44)	(1.42)	(3.20)	(2.61)	(2.61)	(5.99)
SS_TER		-0.956	-0.628		-2.158**	-1.733*		2.218	2.417
		(0.65)	(0.66)		(1.01)	(1.03)		(1.89)	(1.92)
NEWS x SS_TER			-1.880**			-2.256			-1.394
			(0.94)			(1.41)			(2.54)
AbsRet	-2.947	-2.538	-2.014	-0.280	0.616	1.247	-2.799	-3.838	-3.417
	(9.20)	(9.32)	(9.34)	(13.40)	(13.59)	(13.59)	(21.58)	(21.63)	(21.50)
AbnVolRatio	51.503	76.864	84.295	53.698	110.989	120.161	205.473	146.079	151.184
	(48.81)	(49.97)	(51.41)	(66.78)	(74.94)	(77.00)	(143.20)	(146.12)	(147.60)
ES	-4.629***	-4.731***	-4.754***	-3.976**	-4.120**	-4.161**	-8.379	-7.208	-7.114
	(1.02)	(1.01)	(1.01)	(1.69)	(1.65)	(1.66)	(15.02)	(15.26)	(15.27)
Controls & Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
ID & Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm & Date Cluster	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	74,520	74,520	74,520	51,811	51,811	51,811	22,162	22,162	22,162
R^2	0.058	0.058	0.058	0.103	0.103	0.103	0.124	0.124	0.124

Table IA.5: Are Retail Contrarians on News Days?

This table explores the relation between retail order imbalance and returns on news and non-news days. Standard errors are double clustered by firm and date and reported in parentheses below the coefficient estimates. Statistical significance at the 10%, 5%, and 1% level is indicated with *, **, and ***, respectively.

Panel A: Date FE

	NEWS			NO NEWS		
	All	#Trades>1	#Trades Cont.	All	#Trades>1	#Trades Cont.
	(1)	(2)	(3)	(4)	(5)	(6)
RET	-0.128***	0.008	0.035	-0.265***	-0.130***	-0.071**
	(0.04)	(0.04)	(0.04)	(0.02)	(0.02)	(0.03)
CRET t-5 t-1	-0.166***	-0.108***	-0.137***	-0.309***	-0.227***	-0.276***
	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
CRET t-26 t-6	-0.005	0.019	-0.001	-0.026***	-0.003	-0.021***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
LnAveSize t-26 t-5	0.007***	0.012***	0.006**	-0.010***	-0.009***	-0.010***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
#Trades			-0.001***			-0.002***
			(0.00)			(0.00)
Date FE	YES	YES	YES	YES	YES	YES
Firm FE	NO	NO	NO	YES	YES	YES
Firm & Date Cluster	YES	YES	YES	YES	YES	YES
Observations	21,635	12,008	21,635	133,504	56,670	133,504
R^2	0.118	0.156	0.122	0.100	0.130	0.104

Panel B: Date & Firm FE

	NEWS			NO NEWS		
	All	#Trades>1	#Trades Cont.	All	#Trades>1	#Trades Cont.
	(1)	(2)	(3)	(4)	(5)	(6)
RET	-0.020	0.110***	0.154***	-0.184***	-0.047**	-0.009
	(0.04)	(0.04)	(0.05)	(0.02)	(0.02)	(0.02)
CRET t-5 t-1	-0.151***	-0.099***	-0.125***	-0.280***	-0.209***	-0.250***
	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
CRET t-26 t-6	-0.014	-0.006	-0.012	-0.027***	-0.011**	-0.023***
	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)
LnAveSize t-26 t-5	0.013	-0.001	0.015	0.010	0.002	0.013*
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
#Trades			-0.001***			-0.002***
			(0.00)			(0.00)
Date FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Firm & Date Cluster	YES	YES	YES	YES	YES	YES
Observations	21,097	11,446	21,097	133,167	56,133	133,167
R^2	0.259	0.339	0.263	0.186	0.263	0.189

Table IA.6: Retail Order Imbalance and Return Predictability

This table explores the relation between retail order imbalance and return predictability on news and non-news days. Standard errors are double clustered by firm and date and reported in parentheses below the coefficient estimates. Statistical significance at the 10%, 5%, and 1% level is indicated with *, **, and ***, respectively.

Panel A: All Trades - Date FE

	NEWS			NO NEWS		
	(1) CRET1	(2) CRET5	(3) CRET10	(4) CRET1	(5) CRET5	(6) CRET10
OIB	-0.044	0.158	0.247	-0.378***	-0.283***	-0.309***
	(0.07)	(0.13)	(0.17)	(0.04)	(0.07)	(0.10)
RET	-0.015**	-0.041***	-0.023	-0.049***	-0.076***	-0.076***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
CRET t-5 t-1	-0.004	-0.029***	-0.028***	-0.010***	-0.025***	-0.040***
	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
CRET t-26 t-6	-0.003*	-0.004	-0.003	-0.002**	-0.006***	-0.008**
	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
AbnVolRatio	-0.552	-2.388***	-2.960***	-1.201***	-3.333***	-4.012***
	(0.37)	(0.60)	(0.72)	(0.18)	(0.38)	(0.52)
LnAveSize t-26 t-5	0.093***	0.116**	0.139**	-0.045***	0.080**	0.101*
	(0.02)	(0.05)	(0.07)	(0.01)	(0.04)	(0.06)
NEWS Days	YES	YES	YES	NO	NO	NO
Date FE	YES	YES	YES	YES	YES	YES
Firm FE	NO	NO	NO	NO	NO	NO
Firm & Date Cluster	YES	YES	YES	YES	YES	YES
Observations	21,474	21,005	20,425	132,249	129,000	125,331
R^2	0.136	0.174	0.181	0.094	0.150	0.168

Panel B: All Trades - Date & Firm FE

	NEWS			NO NEWS		
	(1) CRET1	(2) CRET5	(3) CRET10	(4) CRET1	(5) CRET5	(6) CRET10
OIB	0.013	0.333**	0.302*	-0.346***	-0.169**	-0.121
	(0.07)	(0.13)	(0.18)	(0.04)	(0.07)	(0.10)
RET	-0.027***	-0.080***	-0.083***	-0.058***	-0.110***	-0.138***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
CRET t-5 t-1	-0.006	-0.045***	-0.048***	-0.015***	-0.043***	-0.072***
	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)
CRET t-26 t-6	-0.005**	-0.011**	-0.015*	-0.004***	-0.014***	-0.019***
	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
AbnVolRatio	0.152	-1.332**	-1.611*	-1.171***	-2.157***	-1.693***
	(0.43)	(0.67)	(0.84)	(0.19)	(0.38)	(0.51)
LnAveSize t-26 t-5	-0.858***	-3.215***	-5.361***	-0.818***	-2.681***	-5.148***
	(0.16)	(0.37)	(0.53)	(0.07)	(0.19)	(0.30)
NEWS Days	YES	YES	YES	NO	NO	NO
Date FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Firm & Date Cluster	YES	YES	YES	YES	YES	YES
Observations	20,934	20,463	19,871	131,915	128,656	124,978
R^2	0.253	0.315	0.325	0.124	0.203	0.243

Panel C: Number of Trades >1 - Date FE

	NEWS			NO NEWS		
	(1) CRET1	(2) CRET5	(3) CRET10	(4) CRET1	(5) CRET5	(6) CRET10
OIB	0.001	0.283	0.306	-0.556***	-0.623***	-0.764***
	(0.12)	(0.25)	(0.31)	(0.08)	(0.15)	(0.21)
RET	-0.020**	-0.043***	-0.029	-0.055***	-0.077***	-0.083***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
CRET t-5 t-1	-0.002	-0.030***	-0.027***	-0.009***	-0.025***	-0.042***
	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
CRET t-26 t-6	-0.002	-0.004	-0.001	-0.002**	-0.007***	-0.009**
	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
AbnVolRatio	-0.268	-2.238***	-2.659***	-1.283***	-3.602***	-3.895***
	(0.40)	(0.64)	(0.78)	(0.22)	(0.42)	(0.57)
LnAveSize t-26 t-5	0.131***	0.153**	0.218**	-0.048***	0.147***	0.201***
	(0.03)	(0.06)	(0.08)	(0.02)	(0.04)	(0.07)
NEWS Days	YES	YES	YES	NO	NO	NO
Date FE	YES	YES	YES	YES	YES	YES
Firm FE	NO	NO	NO	NO	NO	NO
Firm & Date Cluster	YES	YES	YES	YES	YES	YES
Observations	11,900	11,635	11,287	55,981	54,627	53,030
R^2	0.150	0.191	0.197	0.093	0.153	0.175

Panel D: Number of Trades >1 - Date & Firm FE

	NEWS			NO NEWS		
	(1) CRET1	(2) CRET5	(3) CRET10	(4) CRET1	(5) CRET5	(6) CRET10
OIB	0.161	0.640**	0.486	-0.495***	-0.488***	-0.538***
	(0.14)	(0.26)	(0.34)	(0.08)	(0.15)	(0.21)
RET	-0.039***	-0.093***	-0.106***	-0.066***	-0.112***	-0.144***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
CRET t-5 t-1	-0.006	-0.047***	-0.049***	-0.016***	-0.046***	-0.076***
	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)
CRET t-26 t-6	-0.007**	-0.015**	-0.018*	-0.005***	-0.018***	-0.024***
	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
AbnVolRatio	0.439	-1.036	-1.531	-1.285***	-2.242***	-1.587***
	(0.50)	(0.74)	(0.96)	(0.24)	(0.44)	(0.57)
LnAveSize t-26 t-5	-1.199***	-3.679***	-6.279***	-1.120***	-3.403***	-6.206***
	(0.22)	(0.45)	(0.67)	(0.11)	(0.28)	(0.41)
NEWS Days	YES	YES	YES	NO	NO	NO
Date FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Firm & Date Cluster	YES	YES	YES	YES	YES	YES
Observations	11,332	11,066	10,711	55,445	54,092	52,489
R^2	0.302	0.377	0.384	0.149	0.237	0.282

Panel E: Controlling for the Number of Trades - Date FE

	NEWS			NO NEWS		
	(1) CRET1	(2) CRET5	(3) CRET10	(4) CRET1	(5) CRET5	(6) CRET10
OIB	-0.039	0.157	0.215	-0.385***	-0.307***	-0.342***
	(0.07)	(0.13)	(0.18)	(0.04)	(0.07)	(0.10)
RET	-0.017**	-0.041***	-0.014	-0.046***	-0.067***	-0.063***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
CRET t-5 t-1	-0.004	-0.029***	-0.025***	-0.009***	-0.023***	-0.037***
	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
CRET t-26 t-6	-0.004*	-0.004	-0.003	-0.001**	-0.006***	-0.007**
	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
AbnVolRatio	-0.637	-2.381***	-2.350***	-1.073***	-2.876***	-3.385***
	(0.41)	(0.63)	(0.77)	(0.19)	(0.41)	(0.58)
LnAveSize t-26 t-5	0.092***	0.116**	0.147**	-0.044***	0.084**	0.108*
	(0.02)	(0.05)	(0.07)	(0.01)	(0.04)	(0.06)
#Trades	0.001	-0.000	-0.010*	-0.003*	-0.011***	-0.015***
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)
NEWS Days	YES	YES	YES	NO	NO	NO
Date FE	YES	YES	YES	YES	YES	YES
Firm FE	NO	NO	NO	NO	NO	NO
Firm & Date Cluster	YES	YES	YES	YES	YES	YES
Observations	21,474	21,005	20,425	132,249	129,000	125,331
R^2	0.136	0.174	0.182	0.094	0.151	0.168

Panel F: Controlling for the Number of Trades - Date & Firm FE

	NEWS			NO NEWS		
	(1) CRET1	(2) CRET5	(3) CRET10	(4) CRET1	(5) CRET5	(6) CRET10
OIB	0.022	0.343**	0.273	-0.351***	-0.187***	-0.140
	(0.07)	(0.13)	(0.18)	(0.04)	(0.07)	(0.10)
RET	-0.029***	-0.083***	-0.075***	-0.056***	-0.102***	-0.129***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
CRET t-5 t-1	-0.007	-0.046***	-0.046***	-0.015***	-0.041***	-0.070***
	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)
CRET t-26 t-6	-0.005***	-0.012**	-0.015*	-0.004***	-0.013***	-0.019***
	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
AbnVolRatio	-0.012	-1.543**	-0.997	-1.039***	-1.718***	-1.228**
	(0.48)	(0.70)	(0.90)	(0.20)	(0.41)	(0.58)
LnAveSize t-26 t-5	-0.867***	-3.227***	-5.330***	-0.813***	-2.662***	-5.128***
	(0.16)	(0.36)	(0.53)	(0.07)	(0.19)	(0.30)
#Trades	0.003	0.003	-0.009*	-0.003*	-0.010***	-0.010**
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
NEWS Days	YES	YES	YES	NO	NO	NO
Date FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Firm & Date Cluster	YES	YES	YES	YES	YES	YES
Observations	20,934	20,463	19,871	131,915	128,656	124,978
R^2	0.253	0.315	0.325	0.124	0.203	0.243

Table IA.7: Trade Gain - Trader Account and Firm Characteristics

This table reports results from stock-day-trade panel regressions where we regress the net trade gain in percent on a news dummy indicator, ranks based on trader account characteristics and stock characteristics, and other control variables. Panel A explores the relation between account and stock characteristics and trading performance. We rank all 5,182 accounts into terciles based on the total number of trades, percentage of stock trades (of stocks and options trades), and holding period (duration). We then construct indicator variables that receive a value of one if the selected account characteristics are ranked in the top tercile across all accounts. In a similar manner, each day, we cross-sectionally rank all stocks in our sample into terciles based on stock market capitalization, stock turnover, and the previous month's stock returns and construct similar top tercile indicators. Panels B and **??** explore their interactions with news. The sample period is from January 2020 to December 2022. We include firm and account ID fixed effects. Standard errors are double clustered by firm and date and reported in parentheses below the coefficient estimates. Statistical significance at the 10%, 5%, and 1% level is indicated with *, **, and ***, respectively.

Panel A: Trade performance and account and Stock characteristics - main

	Account Characteristics			Stock Characteristics		
	(1)	(2)	(3)	(4)	(5)	(6)
NEWS	-0.123***	-0.126***	-0.113***	-0.124***	-0.126***	-0.126***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
TotActTrd_TopTerDum	0.010					
	(0.05)					
PctStock_TopTerDum		0.086**				
		(0.04)				
SlowTrader_TopTerDum			0.196			
			(0.14)			
Size_TopTerDum				-0.224		
				(0.14)		
Turnover_TopTerDum					-0.148***	
					(0.05)	
PastMonRet_TopTerDum						-0.138***
						(0.04)
PreSignUp Indic	0.177***	0.184***	0.171***	0.179***	0.177***	0.180***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
AbsRet	-0.096**	-0.097**	-0.094**	-0.095**	-0.095**	-0.096**
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
AbnVolRatio	-0.012**	-0.012**	-0.012**	-0.012**	-0.015***	-0.013**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
ES	0.156**	0.157**	0.153**	0.158**	0.152**	0.156**
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Controls	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
ID FE	NO	NO	NO	NO	NO	NO
Firm & Date Cluster	YES	YES	YES	YES	YES	YES
Observations	1,393,955	1,393,955	1,393,955	1,393,955	1,393,955	1,393,955
R^2	0.010	0.010	0.010	0.010	0.010	0.010

Panel B: Trade performance and account stock characteristics - interactions

	Account Characteristics			Stock Characteristics		
	(1)	(2)	(3)	(4)	(5)	(6)
NEWS	-0.252***	-0.141***	-0.068*	-0.166***	-0.115**	-0.156***
	(0.08)	(0.05)	(0.04)	(0.05)	(0.05)	(0.04)
NEWS x TotActTrdDum	0.168**					
	(0.07)					
TotActTrd_TopTerDum	-0.030					
	(0.06)					
NEWS x PctStockDum		0.034				
		(0.06)				
PctStock_TopTerDum		0.078				
		(0.05)				
NEWS x DurationDum			-0.331**			
			(0.17)			
SlowTrader_TopTerDum			0.265*			
			(0.16)			
NewsDum13_TopSizeTER				0.166***		
				(0.06)		
TopSizeTER				-0.253*		
				(0.15)		
NewsDum13_TopToTER					-0.025	
					(0.07)	
TopToTER					-0.142***	
					(0.05)	
NewsDum13_TopAccRetTER						0.092
						(0.07)
TopAccRetTER						-0.160***
						(0.05)
Controls	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
ID FE	NO	NO	NO	NO	NO	NO
Firm & Date Cluster	YES	YES	YES	YES	YES	YES
Observations	1,393,955	1,393,955	1,393,955	1,393,955	1,393,955	1,393,955
R^2	0.010	0.010	0.010	0.010	0.010	0.010

Table IA.8: Trade performance and other account characteristics

This table reports results from stock-day-trade panel regressions where we regress the net trade gain in percent on a news dummy indicator, ranks based on other account characteristics, and other control variables. Panel A explores the relation between account characteristics and trading performance. We use all 5,182 accounts to construct a set of additional indicator variables. "FastTrader" is an indicator that receives the value of one if the median trade duration $<$ 1 day. "SlowTrader" is an indicator that receives the value of one if the median trade duration $>=$ 1 day. "LowStakes" is an indicator that receives the value of one if the median trade size $<$ \$200. "HighStakes" is an indicator that receives the value of one if the median trade size $>$ \$5,000. "FewTrades" is an indicator that receives the value of one if the median number of trades in a month $<$10. "ManyTrades" is an indicator that receives the value of one if the median number of trades in a month $>$30; and "joint" is an indicator that receives the value of one if an account trades stocks and options. Panel B explore their interactions with news. The sample period is from January 2020 to December 2022. We include firm and account ID fixed effects. Standard errors are double clustered by firm and date and reported in parentheses below the coefficient estimates. Statistical significance at the 10%, 5%, and 1% level is indicated with *, **, and ***, respectively.

Panel A: Trade performance and other account characteristics - main

	Other Account Characteristics - Main Effect					
	(1)	(2)	(3)	(4)	(5)	(6)
NEWS	-0.095***	-0.124***	-0.124***	-0.122***	-0.120***	-0.125***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Slow Trader	0.625***					
	(0.19)					
Low Stakes		-0.098				
		(0.14)				
High Stakes			0.214***			
			(0.03)			
Few Trades				0.100		
				(0.10)		
Many Trades					-0.138***	
					(0.05)	
Joint						-0.052
						(0.05)
Controls	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
ID FE	NO	NO	NO	NO	NO	NO
Firm & Date Cluster	YES	YES	YES	YES	YES	YES
Observations	1,393,955	1,393,955	1,393,955	1,393,955	1,393,955	1,393,955
R^2	0.011	0.010	0.010	0.010	0.010	0.010

Panel B: Trade performance and other account characteristics - interactions

	Other Account Characteristics - Main Effect and Interaction					
	(1)	(2)	(3)	(4)	(5)	(6)
NEWS	-0.045	-0.092**	-0.125***	-0.104***	-0.237***	-0.129***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.07)	(0.04)
News X Slow Trader	-0.749***					
	(0.24)					
Slow Trader	0.753***					
	(0.21)					
News X Low Stakes		-0.924***				
		(0.21)				
Low Stakes		0.087				
		(0.15)				
News X High Stakes			0.010			
			(0.05)			
High Stakes			0.212***			
			(0.04)			
News X Few Trades				-0.252*		
				(0.14)		
Few Trades				0.159		
				(0.12)		
News X Many Trades					0.165***	
					(0.06)	
Many Trades					-0.178***	
					(0.05)	
News X Joint						0.011
						(0.07)
Joint						-0.055
						(0.06)
Firm FE	YES	YES	YES	YES	YES	YES
ID FE	NO	NO	NO	NO	NO	NO
Firm & Date Cluster	YES	YES	YES	YES	YES	YES
Observations	1,393,955	1,393,955	1,393,955	1,393,955	1,393,955	1,393,955
R^2	0.011	0.010	0.010	0.010	0.010	0.010