A Pond for Small Fish?

News and (Retail) Trading After-Hours

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ABSTRACT

We explore after-hours trading (AHT) in the U.S. equity market, focusing on the effect of AHT news releases on market quality. We show that scheduled and positive after-hours firm-specific news catches the attention of retail participants. We use a machine learning algorithm on Robinhood retail popularity to construct a new measure of retail activity during AHT. We identify the buyer-initiated odd-lot trades on the CBOE exchange, which offers a platform (EDGX) with retail priority, as the main predictor of AHT retail activity. The second extension of trading hours on the Robinhood platform provides additional support for retail identification. The introduction of retail priority on the CBOE EDGX platform significantly reduces profits to liquidity provision on earnings news days with high AHT return volatility, suggesting picking-off risk for retail traders.

Keywords: After-hours trading, news, Robinhood, machine learning, retail priority.
JEL classification: G10, G12, G14.

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Incorporating news into prices is a fundamental function of financial markets and is a key indicator of market efficiency. Due to the increase in online and mobile media outlets, market participants have access to more news about corporate events over time. However, given the limited attention of market participants in a world with abundant news, the type and the timing of news releases become increasingly important (Liu et al., 2023).[1] Although most of the trading activity takes place during regular trading hours (RTH), both exchanges and alternative trading platforms offer trading beyond these hours, particularly in the after-hours market.[2] Firms release important corporate news via scheduled and unscheduled announcements more frequently outside RTH (see Figure 1). It is therefore surprising that after-hours trading (AHT) has received relatively little attention, particularly around news releases.[3]

[Figure 1 about here.]

How distinct is AHT from trading during RTH in terms of liquidity? What types of corporate AHT news drive AHT activity? Can we trace retail trading after markets close? Do retail traders react to AHT news? If yes, is it a good idea to provide liquidity on news days? We answer these questions by shedding light on the AHT activity of a large cross-section of U.S. firms (i.e., constituents of the S&P 1500 index) over a long time series (2004–2022), with a particular focus on the recent post-2018 period. While many studies document the market quality of regular trading hours (e.g., Chordia et al., 2011), with a recent focus on market close (Comerton-Forde and Rindi, 2022; Bogousslavsky and Muravyev, 2023), there is scant evidence on how trading evolves in the after-hours market, especially retail trading in recent years.

[1] There is evidence that firms strategically choose when to disclose material news (e.g., Cuñat and Groen-Xu, 2025; Edmans et al., 2018; Johnson and So, 2018; Michaely et al., 2014).

[2] In May 2023, the Robinhood platform started offering 24 Hour market. The New York Stock Exchange (NYSE) also started the conversation around round-the-clock (24/7) trading (Financial Times, 2025).

[3] One important exception is Boudoukh et al. (2019) where the authors show the importance of firm-specific news on volatility by comparing news arrival overnight vs. during trading hours.

The landscape for AHT has changed substantially over time. According to a Securities Exchange Commission (SEC) report in 2000, a large part of AHT occurred on regular exchanges. However, we note that the picture is different today: earlier tick size changes around the millennium initiated a trend in AHT on off-exchange electronic communication networks (ECN) (Conrad et al., 2003) with a further boost following the Regulation NMS starting in 2005 that resulted in more fragmentation in U.S. equity markets.[4] In Figure 2 we document an increase in AHT activity at the beginning of the sample, in particular after 2005, around the Regulation NMS, followed by a decline due to the Global Financial Crisis, and a gradually increasing pattern until the end of 2017. The AHT volume in aggregate (for S&P 1500 firms) has nearly doubled since 2017 and was particularly high in the last two years of our sample.

The number of AHT trades by venue in Panel B shows that the trading is fragmented across venues. Exchanges (CBOE EDGX, NASDAQ, NYSE) attract small trades, while larger trades are executed on off-exchange venues (FINRA). We note that the number of trades more than doubled during the Covid-19 pandemic in 2020, with a notable increase in trades on CBOE EDGX exchange. In this paper, we test whether the new entry of retail traders in AHT has contributed to the sharp increase in recent years.

[Figure 2 about here.]

After-hours trading (AHT) could in principle appeal to different types of traders, including institutional, retail, and high-frequency traders (HFT). The last group was less active in AHT until recently (Cole et al., 2015), however, one cannot rule out HFT participation if retail traders are present during AHT (Eaton et al., 2022; Scharnowski, 2024) and if HFTs have a comparative advantage in processing public news (Baldauf and Mollner, 2022; Huang et al., 2023) or anticipate retail trades (Hirschey, 2021). Yet, there is little direct evidence of trader composition after markets close, especially around different types of firm-specific news

[4] In 2007, the National Association of Securities Dealers (NASD) evolved into the Financial Industry Regulatory Authority, Inc. (FINRA), a private self-regulatory organization to which broker-dealers and ECNs report their trades via the Alternative Display Facility (ADF).

events.[5] Brokerage firms often publish a disclosure statement to warn retail traders against the dangers of AHT, such as low liquidity (e.g., wider spreads), high volatility, disconnection with other markets, and abrupt changes in prices that are often linked with news arrival.[6] Nonetheless, zero-commission trading platforms facilitate easy access to AHT (Mantel and Saglam, 2024).

We provide a comprehensive overview of AHT activity by collecting information on both *scheduled* firm-specific news, such as earnings news (Cole et al., 2015; Jiang et al., 2012), and *unscheduled* corporate news events (Baruch et al., 2017; Huang et al., 2020), such as insider trading news. Using a detailed news dataset collected by RavenPack, we look into news articles disseminated in the AHT for S&P1500 stocks during the period January 5, 2004, and October 31, 2022, as well as a more recent sample from 2018. Between May 2, 2018, and August 13, 2020, we also observe retail investor holdings on the Robinhood platform via Robintrack. We confirm that a greater number of news releases over time during AHT coinciding with higher AHT trading activity with lower spreads, except the price impact component reflecting a potential increase in adverse selection due to news arrival (Biais et al., 2015; Foucault et al., 2016; Colliard et al., 2022). We distinguish between good and bad news using RavenPack sentiment scores. We show that AHT activity and liquidity differ substantially on news days; trades nearly double on news days with lower spreads. Good news attracts more trades, although the gap is diminishing in the recent sample. Trades nearly triple on days with scheduled news, five times higher on days with earnings news compared to days with insider trading news in the pre-2018 sample, however, this difference is also narrower in the recent sample. AHT returns, volatility and next-day returns reflect the AHT news sentiment, but the reaction of returns to AHT news, especially earning news,

[5]Retail traders are encouraged to trade using limit orders. Many brokerage firms only allow for limit orders in the after-hours market (SEC Bulletin, 2011). Liquidity provision is competitive during after-hours while liquidity remains scarce (Barclay and Hendershott, 2004). Several papers capture retail activity with marketable orders (Boehmer et al., 2021) or fractional trades (Bartlett et al., 2024; Da et al., 2024). However, most platforms allow AHT only via limit orders, and fractional shares are only executed during regular trading hours.

[6]FINRA members are obliged (FINRA Rule 2265) to disclose their Extended Hours Trading Risk Disclosure Statements.

has declined in the recent sample, presumably thanks to the increased liquidity.

On August 1, 2018, the Robinhood platform allowed all its regular customers to trade until 06:00 p.m. EST, extending trading on the platform beyond the market close at 04:00 p.m.[7] We use this event in a difference-in-difference (DiD) setting to test the retail reaction to different types of AHT firm-specific news of individual stocks. We show that AHT news, especially positive and scheduled news such as earnings news, drives retail access via the Robinhood AHT platform. The news-based increased AHT popularity is consistent with the attention-induced "uninformed retail investors hypothesis" (Barber et al., 2022; Jones et al., 2023; Pedersen, 2022) where (good) corporate news attracts retail participation.

Measuring retail trading activity without proprietary datasets (e.g., using TAQ data) remains an important challenge (Barber et al., 2024a; Battalio et al., 2024). We propose a measure to capture the retail trading activity during AHT, retail trading intensity (RTI). Following Bogousslavsky et al. (2024), we adopt a data-driven machine learning approach to evaluate which microstructure variables have the most explanatory power to detect retail trading during AHT. Recent studies such as Boehmer et al. (2021) and Barber et al. (2024b) measure retail trading during RTH using high-frequency data based on market orders. Since investors can only use limit orders during AHT, proposed retail measures cannot be constructed for AHT. The machine learning method reveals that the number of buyer-initiated odd-lot trades during AHT from a particular exchange, that is, the CBOE EDGX exchange that offers a platform with retail priority (CBOE, 2024), is the most important predictor of retail popularity.[8]

We further provide evidence of the reaction of odd-lot trades to different types of news. We see a particular increase in odd-lot trades on CBOE EDGX exchange around the Covid-19 period coinciding with the entry of retail traders during the pandemic. Yet, the rise in odd-lot trades on all platforms on news days makes the retail identification based on

[7]Before this date, this feature was only available to exclusive Robinhood Gold customers.

[8]We repeat the same analysis using data only from RTH and the results suggest that signed retail trades based on Boehmer et al. (2021) rather than odd-lot trades are one of the main predictors of RTH retail popularity.

exchanges challenging. Not only retail, but also algorithmic traders and HFTs often use odd-lots (e.g., Bartlett et al., 2025; O'hara et al., 2014). We circumvent this problem, by focusing on the Robinhood platform's second extension of the trading hours to 08:00 p.m. EST. We test if the buyer-initiated odd-lot trades help us identify retail activity driven by firm-specific news releases. Our results confirm that odd-lot trades from the CBOE EDGX exchange provide a strong signal for retail participation in AHT on firm-specific news days.

The introduction of retail priority on CBOE EDGX exchange on November 1, 2019, reveals that profits to liquidity provision measured by realized spreads decrease significantly on days of AHT earnings announcements, but only on the CBOE EDGX exchange. The reduction comes from stocks with high AHT return volatility. This provides compelling evidence of limit orders with retail priority exposing retail traders to picking-off risk on days of uncertain earnings news, working as bait for other opportunistic traders. We then provide microscopic evidence on intraday AHT liquidity provision around two events: i) Apple's (AAPL) earnings news on July 30, 2020, at 04:30 pm EST[9] and ii) Gamestop (GME) frenzy on January 26, 2021, triggered by Elon Musk's tweet "GameStonk" at 04:08 pm EST. The tale of two events helps us compare the reaction of market participants on different exchanges to scheduled and unscheduled news events. This analysis shows that retail traders have limited ability to enjoy retail priority in liquidity provision as more sophisticated traders exploit low-latency technology to react to public news. In general, our results suggest that event-driven market participation in after-hours markets may not be the right choice for retail traders to participate in AHT liquidity provision on volatile days.

The remainder of the paper is organized as follows; Section I introduces the data sources. Section II describes the AHT trading and the AHT news information environment, III links firm-specific news to AHT retail trading. Section IV provides an intraday analysis of two events. Section V concludes.

[9]We also extend the analysis to a larger set of earnings news events.

I. Data

Our data come from a variety of sources. For regular trading hours, we use the WRDS Intraday Indicators to obtain the data. For after-hours, we use the DTAQ to collect intraday (millisecond) transactions and quotations. To provide evidence on AHT and to compare RTH and AHT, we use trade executions for the constituents of the S&P Composite 1500 index for the period January 5, 2004 to October 31, 2022. Regular trading hours (RTH) refers to trading sessions from 09:30 a.m. to 04:00 p.m. EST. After-hours trading (AHT) refers to a trading session from 04:00 p.m. to 08:00 p.m. EST. NYSE "Closing auction" and NASDAQ "Closing cross" are printed in DTAQ with timestamps right after 04:00 p.m., but we eliminate these trades from the analysis of AHT because they represent different trading mechanisms. The procedure to eliminate closing auction trades and the relevant filters are detailed in Internet Appendix A.A.1. We also deliberately eliminate pre-open trades since the pre-open market attracts a different clientèle and hence exhibits substantially different trading characteristics (Barclay and Hendershott, 2008). We exclude holidays when the market closes or closes early.[10] Our final sample consists of 6,906,378 stock-day observations for S&P1500 index stocks. In Internet Appendix A.A.2, we explain how we construct liquidity measures from intraday data.

We obtain news sentiment data from RavenPack (e.g., Chordia et al., 2024; Chinco et al., 2019) which is a comprehensive news dataset containing real-time news releases for stocks listed on the NYSE, AMEX, and NASDAQ. RavenPack collects and analyzes real-time, firm-level business news from leading news providers (e.g., Dow Jones Newswire, The Wall Street Journal, and Barron's) and other major publishers and web aggregators, including industry and business publications, regional and local newspapers, government and regulatory updates, and trustworthy financial websites. These news releases are related to corporate news events commonly used by institutional and individual investors. Note that a corporate news

[10]The holidays are New Year's Day, Martin Luther King Day, Washington's Birthday, Good Friday, Memorial Day, The Day before Independence Day, Independence Day, Labor Day, Thanksgiving Day, Black Friday, Christmas Eve, and Christmas Day.

event may be reproduced and disseminated through many news articles. RavenPack also provides a score by systematically matching stories typically categorized by financial experts as having a short-term positive or negative financial or economic impact. The strength of the score is derived from a collection of surveys in which industry experts with extensive backgrounds in finance and economics rate entity-specific events as conveying positive or negative sentiment and to what degree. Their ratings are encapsulated in an algorithm that generates a score ranging from 0-100, where 50 indicates neutral sentiment, values above 50 indicate positive sentiment, and values below 50 show negative sentiment. We focus on firm-relevant news by setting the news-relevance score (G_NRS) to 100.

We collect stock-level controls from CRSP, such as price and market capitalization. In the recent sample, from June 2018 to August 2020, we have a direct measure of retail popularity from retail brokerage firm, Robinhood via the Robintrack website. We measure AHT retail popularity as the absolute value of the difference in the number of users holding S&P 1500 constituents on Robinhood for each day between 04:00 p.m. and 08:00 p.m.

II. AHT Activity

We start with a comparison of trading activity during RTH and AHT. Most of the evidence on trading activity and market quality of RTH in recent years has already been documented in earlier papers (e.g., Chordia et al., 2011). We report here RTH activity as a benchmark to assess the recent evolution of AHT, a relatively unexplored territory. Although some recent studies allude to the importance of AHT activity in the context of corporate announcements (Cuñat and Groen-Xu, 2025; Jiang et al., 2012) and price discovery (Barclay and Hendershott, 2003; Gregoire and Martineau, 2022), relatively little is known about the microstructure of the after-hours market.

In Table I we provide the summary statistics for the trading activity and intraday liquidity measures for the sample period, January 5, 2004 - October 31, 2022, for all stocks. We report

both the equal-weighted and value-weighted averages across S&P 1500 constituents. We first note the striking differences between RTH and AHT trading activities: on average (value-weighted) significantly less, 24.26 (153.43) vs. 10.85 (47.09) thousand trades, and $3.5 ($27.3) million vs. $90.08 ($569.93) dollar volume, take place during AHT. This indicates that the two markets are substantially different in terms of trading activity. The larger value-weighted average suggests that larger stocks have more active after-hours markets. The range (99^{th} percentile) of dollar volume in AHT shows that it can occasionally attract very large trading volume. Liquidity measures also draw a similar picture, suggesting that AHT is shallower with higher transaction costs measured in quoted, effective, and realized spreads. The AHT realized spread is a larger fraction of the AHT effective spread reflecting the profitability of liquidity provision. However, the larger AHT price impact, primarily driven by the larger values in the right tail, highlights the potential picking-off risk associated with firm-specific news arrival.

[Table I about here.]

A. Firm-specific news

We next explore the link between firm-specific news and AHT activity. We provide the list of corporate news events identified by RavenPack. Table II shows the count and frequency of news events and news articles related to different firm-specific news events during RTH and AHT along with the fraction of scheduled news and the ratio of bad over good news based on the RavenPack news sentiment indicator.

[Table II about here.]

We observe some interesting facts. The top two AHT news events are related to insider trades and earnings news. Both types of news contain important fundamental firm-specific information. Among the top 22 news categories covered in RavenPack for S&P 1500 stocks during our sample period (January 5, 2004 - October 31, 2022), AHT news events constitute

around one-third of all news events. For the top two news categories, there are more AHT news events compared with RTH news. All insider trading news are unscheduled news events, while %93 of earnings news events are scheduled. Together the top two categories capture nearly half of all news events during AHT. While proportionally fewer negative earnings announcements are made during AHT compared with those during RTH (Michaely et al., 2014), the opposite is true for insider trading news. This suggests that more insider sales are filed during AHT (Biggerstaff et al., 2020). The former evidence contrasts with the earlier view (Gennotte and Trueman, 1996; Patell and Wolfson, 1982) that firms time their earnings announcements strategically by hiding bad earnings announcements in a low-attention period. These observations show that the study of AHT activity is important since information releases are increasingly taking place during AHT (as shown in Figure 1).

B. News and AHT

Does the AHT trading react to news released after markets close? Does the reaction depend on the news type? There is a broad literature showing news induces attention-driven demand (e.g., Fang and Peress, 2009; Fedyk, 2022) not only by retail traders but also by institutions (Ben-Rephael et al., 2017; Huang et al., 2020). If market participants pay attention to AHT news, it should be reflected in trading activity and liquidity.

In Table III, we present how the trading activity and spread measures change across news types over two sub-samples. Panel A covers the period from January 5, 2004, to July 31, 2018, while Panel B covers the period from August 1, 2018, to October 31, 2022. The variable News is a dummy variable, equal to 1 if a news event is announced during after-hours trading (AHT), and 0 if no news is announced or if neutral sentiment news is reported during regular trading hours (RTH). We define Good News (Bad News) if the accumulated adjusted RavenPack news sentiment scores from 4:00 p.m. to 8:00 p.m. EST take a value of 50 to 100 (0 to 50). We use RavenPack's classification to distinguish between scheduled and unscheduled news events and exclude days with overlapping scheduled and unscheduled news

in case of unscheduled news. Earnings news includes scheduled earnings announcements, but may also include other unscheduled news related to the earnings announcement. For insider trading, we only include insider-buy or insider-sell news, we exclude the days if there is both insider-buy and insider-sell news on the same day.

[Table III about here.]

We first note that the increase in trading activity documented above in Figure 2 in the recent post-2018 period is associated with reduced spreads, except the price impact component of the effective spread. While price impact is expected to increase with the elevated volume of the news releases in the recent sample, it is surprising that the price impact is also higher on no-news days, perhaps reflecting the increased adverse selection risk in AHT. News days attract almost twice as much trading activity, with lower spreads (apart from the price impact component), with an increasing gap in the recent sample. Good news catches slightly more attention, but the spreads are similar in both sub-samples. We see that RTH news is also an important driver of AHT activity, especially in the recent period. As expected, trading is more elevated on scheduled news days such as earnings news, but it is important to note that trading activity more than tripled in the recent sample on days with insider trader news with substantial trading volume.

C. Market Reaction to AHT News

Do the stock returns react to news released after markets close? Does the reaction depend on the news content? There is a broad literature showing news induces attention-driven demand (Fang and Peress, 2009; Tetlock, 2007; Heston and Sinha, 2017; Fedyk, 2022) not only by retail traders but also by institutions (Ben-Rephael et al., 2017; Huang et al., 2020). If market participants pay attention to AHT news, we expect returns to reflect news-driven trading activity.

We explore the information content of news articles disseminated by media outlets during

AHT. We test whether AHT returns, volatility, measured as absolute returns[11] and next-day RTH returns are sensitive to news releases after markets close. We consider next-day abnormal returns using the Fama&French (FF) six-factor (2x3) portfolio formed on size and book-to-market model.[12] We split the days into good-news, and bad-news, distinguish between scheduled and unscheduled news, and also report the sub-sample of earnings and insider trading news based on the sentiment on the sentiment scores provided by RavenPack. We take the days with no news as the baseline, and report results relative to the no-news baseline. We show results for both pre-2018 (from January 5, 2004 to July 31, 2018) and post-2018 (from August 1, 2018 to October 31, 2002).

[Table IV about here.]

We first observe that AHT returns, volatility, and next-day returns reflect the AHT news sentiment; the returns are positive (negative) when good (bad) news arrives in the AHT market, with heightened volatility, reflecting the risk associated with news-driven trades (e.g. Fedyk, 2021; Fedyk and Hodson, 2023). We see a stronger return reaction on days with scheduled news, especially on days with earnings news. We also note that the return reaction to news sentiment has diminished in the recent sample, mainly driven by earning news, reflecting the increased AHT liquidity in the post-2018 sample. The sign of the next-day returns is also in line with news sentiment, suggesting that AHT news is an important driver of next-day RTH price continuation.

III. Retail Access and AHT

So far we have documented that trading is more costly (e.g., higher spreads) for liquidity takers and potentially risky for liquidity providers since different types of AHT news induce

[11] We also repeated the same analysis using range volatility. Results are not sensitive to this choice, available upon request.

[12] We also repeated the same analysis using the single-factor Market model. Results are available upon request.

more AHT. Good (bad) news creates buying (selling) opportunities with predictable gains during AHT. However, faster access to news can generate adverse selection (Biais et al., 2015; Foucault et al., 2016), especially for retail traders who can only provide liquidity via limit orders during AHT. We next explore whether after-hours firm-specific news attracts retail traders. If yes, does the retail reaction to firm-specific AHT news depend on the news types?

To study the effect of retail access on AHT, we divide the section into three parts: (i) we focus on the interaction between retail activity on the Robinhood platform and news releases during AHT (ii) we construct a retail trading intensity (RTI) measure using a large set of microstructure variables in a data-driven machine learning framework, and look for the key drivers (i.e., main feature) of retail activity that helps us identify retail trades during AHT and (iii) we provide external validity for the measures by examining the extension of AHT on the Robinhood platform.

A. AHT News and Robinhood Platform

There is growing literature using data from the Robinhood platform via the Robintrack website to better understand retail participation.[13] Robinhood is a retail brokerage firm that provides information on retail trader participation on its platforms for the sample between May 2018 and August 2020. Several recent studies have used this dataset to analyze retail trading during RTH (e.g., Barber et al., 2022; Fedyk, 2022; Michels, 2025; Welch, 2022). For example, Welch (2022) shows that retail traders invest in stocks with high past volume and extreme past performance, and argues that Robinhood traders acted relatively calmly during the Covid-19 market crash. Barber et al. (2022) provide evidence for attention-induced trading by retail traders. Jones et al. (2023) provide a comprehensive list of papers using both Robinhood data and alternative measures of retail activity to summarize the findings in the literature on the informational content (i.e., short and long-term return predictability)

[13]For details about the platform see, for example, Barber et al. (2022), Eaton et al. (2022), Welch (2022) and Fedyk (2022).

of retail trades and their implication on market quality (e.g., price discovery and liquidity).

On August 1, 2018, the Robinhood platform allowed all its users to trade in the after-hours market from 04:00 p.m. to 06:00 p.m. We use a DiD setting to test the interaction of AHT news releases and retail access on the Robinhood platform. We estimate the following DiD regression using a 60-day window around the introduction of AHT on the Robinhood platform:

$$y_{i,t} = \alpha_i + \gamma_t + \beta_1 RH_t^{AHT} + \beta_2 news_{i,t}^{AHT} + \beta_3 RH_{i,t}^{AHT} \times news_{i,t}^{AHT} + \epsilon_{i,t} \tag{1}$$

The dependent variable $y_{i,t}$ is the AHT popularity of the stock i on day t on the Robinhood platform, $Popularity_{i,t}^{AHT}$. RH_t^{AHT} is a dummy variable equal to one for days between August 1, 2018 and September 13, 2018, and zero for days between June 18, 2018 and July 31, 2018. $News_{i,t}^{AHT}$ is a dummy variable when there is firm-specific news announced during AHT, and no news announced or daily neutral news sentiment during RTH from RavenPack. *No News* refers to no news announcements or an accumulation of neutral news in AHT and RTH. RH_t^{AHT} x $News_{i,t}^{AHT}$ is the interaction term between RH_t^{AHT} and $News_{i,t}^{AHT}$. We also include Good News (Bad News) which is defined as the accumulated adjusted RavenPack news sentiment score between 04:00 pm and 08:00 pm when it falls between 50 and 100 (0 and 50). We use RavenPack's classifications to distinguish between scheduled and unscheduled news events, excluding days with overlapping scheduled and unscheduled news in case of unscheduled news. *No News* refers to no news announcements or having accumulated neutral news in AHT and RTH. We include time (Weekday) and firm fixed effects in the specification.

[Table V about here.]

Table V shows the results for Robinhood popularity using a set of different news types. Our main focus is on the coefficient of the interaction term, β_3. We see that AHT stock popularity increases on news release days once retail access is facilitated. Good news, scheduled

news, and especially earnings news attract retail participation in the after-hours market. We do not see the same effect on the days of negative AHT news or unscheduled news such as insider trading news, the latter two are only significant at the 10% level.[14] These results are suggestive of naive news chaser retail investors (Barber and Odean, 2008; Chordia et al., 2024) and in line with the attention-induced "retail investors hypothesis" (Jones et al., 2023; Pedersen, 2022) where good anticipated corporate news attracts retail participation.

B. Retail Trading Intensity (RTI)

Recent studies such as Boehmer et al. (2021) and Barber et al. (2024b) measure retail trading during RTH using high-frequency data based on market orders. Since investors can only use limit orders during AHT, proposed retail measures are not suitable for AHT. In this study, we construct a measure to capture the retail trading activity during AHT. Following Bogousslavsky et al. (2024), we adopt a data-driven machine learning approach to evaluate the explanatory power of a large set of microstructure variables to detect Retail Trading Intensity (RTI) during AHT.

We implement a random forest (RF) machine learning algorithm incorporating data from the Robinhood platform. In particular, we train the algorithm on the Robinhood dataset to determine the importance of explanatory variables (i.e., features) in explaining the retail popularity during AHT. We select 37 variables (plus five variables at the venue level) from both RTH and AHT described in Internet Appendix Table A.A.3. Four variables are from CRSP daily files, 18 variables are from WRDS Intraday Indicators, and we construct the remaining 13 variables (plus the five variables at the venue level) using TAQ dataset. Overall, 19 (23) variables are related to AHT (RTH). We standardize all variables to ensure comparability across stocks and enhance their interpretability. Our target variable is the absolute value of the difference in the number of users holding S&P 1500 constituents on Robinhood for each day between 04:00 p.m. and 08:00 p.m. from May 3, 2018, to August

[14] If we repeat the analysis with salient unscheduled news, focusing on the news with extreme RavenPack sentiment in the top and bottom sentiment terciles, we obtain significant interaction term at the 5% level.

13, 2020.

In recent years, the adoption of machine learning algorithms in finance has grown rapidly. Breiman (2001) has proposed the RF algorithm which combines decision tree models with the bootstrap RF algorithm due to its robustness in dealing with complex datasets, capacity to capture non-linear relationships, resistance to overfitting, and most importantly its capability to offer rankings of feature importance Hastie et al. (2017). These rankings are instrumental for comprehending the influence of explanatory variables on target variables in our setting.

In Panel A of Figure 3 presents the feature importance of the random forest algorithm where the target variable is AHT retail popularity and features are a set of 37 contemporaneous daily variables constructed from intraday data. The feature importance results reveal that the number of buyer-initiated odd-lot trades in AHT is the most important feature by a large margin.[15] It contributes more than half (56.05%) of the model's predictive power, suggesting it is a crucial determinant of AHT retail popularity. While buyer-initiated small trades have been used as a retail proxy before the entry of algorithmic traders (Barber et al., 2008), these trades cannot be initiated by retail investors in AHT since they can only be on the passive side of the trade as liquidity providers. The second most important feature (10.41%) is the retail order imbalance during RTH (Boehmer et al., 2021). This is consistent with the finding in Table III highlighting the role of RTH news on AHT activity. Other features have only incremental contributions to determine AHT retail popularity. When we repeat the same analysis in Panel B of Figure 3 replacing the total buyer-initiated odd-lot trades, with the buyer-initiated odd-lot traders at venue levels, we see that CBOE (followed by FINRA) stands out as the exchange where these trades are initiated. This result is interesting since the CBOE EDGX platform offers priority to its retail customers. However, it begs the question of whether this priority serves as bait for other opportunistic traders.

[15] As robustness checks, we show the surrogate tree (Internet Appendix Figure B.1), the Shap value (Internet Appendix Figure B.2), implement the Extreme Gradient Boosting (XGBoost) algorithm (Internet Appendix Figure B.3), conduct a 5-fold cross-validation (Internet Appendix Figure B.4), include odd-lot trades without a trade sign (Internet Appendix Figure B.5), and include only the constituents of S&P 500 index (Internet Appendix Figure B.6). All the results confirm the importance of CBOE odd-lot trades.

[Figure 3 about here.]

We assess the performance of our model in an out-of-sample setting. To do that, we split the 90% of our sample period as training (80%) and test sample (20%), and the remaining 10% as the prediction sample. Figure 4 illustrates the average Robinhood popularity and forecasted RTI values. It shows that out-of-sample RTI forecasts are very close to actual popularity measures with a correlation of 0.90%.

[Figure 4 about here.]

As a comparison, we repeat the same analysis using data only from RTH. The results in Appendix Figure B.7 show that signed retail trades based on Boehmer et al. (2021) rather than odd-lot trades appear to be one of the main features to capture RTH Robinhood retail popularity. It is important to note that the accuracy out-of-sample forecasts using RTH retail trading intensity is lower (85% correlation) compared to the forecasts from AHT.

C. Odd-lot Trades

The data-driven RF machine-learning algorithm in the previous section reveals that AHT odd-lot trades, particularly those initiated on the CBOE EDGX platform, are informative about AHT retail activity. How likely is it to observe odd-lot trades? Does it depend on the exchange or news days? In Panel A of Figure 5 we show the heatmap of the value-weighted average of an odd-lot to total trade ratio across venues and different types of news over the sample from August 1, 2018, to October 31, 2022. We split the news into good and bad news based on the RavenPack news sentiment score as above.

[Figure 5 about here.]

We first observe that FINRA (ADF) which attracts the largest dollar volume (see Panel A of Figure 2) and hence likely to include institutional trades has the lowest odd-lot ratio. A large fraction (over 75%) of the CBOE EDGX and NASDAQ trades are odd-lot trades, and

NYSE ARCA lies between FINRA and the other two exchanges. We also see that the odd-lot ratio does not change much across news types, though unscheduled news, e.g., insider trades, trigger a larger fraction of odd-lot trades. When we plot the time series of the odd-lot total trade ratio (Panel B of Figure 5) regardless of news releases, we see that the odd-lot ratio has increased substantially over time, with the largest variation in the CBOE EDGX odd-lot trades, particularly around Covid-19 period, ranging from February 3, 2020 to September 29, 2020, lending further support that CBOE EDGX odd-lot trades are indicative of AHT retail activity.

We next examine the market's reaction to the AHT news in terms of the total number of buyer-initiated odd-lot trades as well as trades across exchanges. We focus on a window of five days before and five days after a news event. The variable News is a dummy variable, taking the value of 1 if a news event is announced during after-hours trading (AHT) and 0 if there is no news or if daily neutral sentiment news is reported during regular trading hours (RTH), as classified by RavenPack. The sample period spans from August 1, 2018, to October 31, 2022.

To estimate the impact of news events, we employ a two-way fixed effects regression model with both firm and day-fixed effects, clustering standard errors by firm and date to account for potential within-group correlation. The model includes a constant, which captures the average effect on days outside the event window (i.e., on all other days in the dataset). The regression model is as follows:

$$y_{i,t} = \beta_0 + \beta_1 news_{i,t}^{AHT} + \beta_{2-6} Lag_{i,t-1,t-5}^{news} + \beta_{7-11} Lead_{i,t+1,t+5}^{news} + \epsilon_{i,t} \tag{2}$$

where $y_{i,t}$ is the number of buyer-initiated odd-lot trades, $Lag_{i,t-1,t-5}^{news}$ and $Lead_{i,t+1,t+5}^{news}$ are the dummy variables indicating the 5-day window around the news event.

[Figure 6 about here.]

The figure shows that AHT news triggers buyer-initiated odd-lot trades across venues,

posing a challenge for retail identification, a concern we address in the next section.[16]

D. *Robinhood Second Extension of AHT hours*

On Mar 29, 2022, the Robinhood platform extended the trading hours for all traders from 04:00–06:00 p.m. to 04:00–08:00 p.m. EST (Mantel and Saglam, 2024). Suppose the odd-lot trades on the CBOE EDGX platform, help us identify retail activity. In that case, an increase in CBOE odd-lot trades would be expected during extended trading hours, especially on the days of firm-specific news releases.

We use a DiD setting to test the effect of interaction between extended retail access on the Robinhood platform and AHT news releases on odd-lot trades. We estimate the following DiD regression using a 60-day window around the AHT extension date on the Robinhood platform:

$$y_{i,t} = \alpha_i + \gamma_t + \beta_1 RH^{AHT}_{t,ext} + \beta_2 news^{AHT}_{i,t} + \beta_3 RH^{AHT}_{t,ext} \times news^{AHT}_{i,t} + \epsilon_{i,t} \tag{3}$$

The dependent variable $y_{i,t}$ is the total buyer-initiated (Panel A) and seller-initiated (Panel B) odd-lot trades from 06:00 pm to 08:00 p.m. EST (normalized by the trades from 04:00 pm to 06:00 p.m.) of stock i on the day t (as well as trades at each venue, i.e., CBOE, FINRA, NASDAQ, and NYSE). $RH^{AHT}_{t,ext}$ is a dummy variable equal to one for days between March 29, 2022, and May 10, 2022, and zero for days between February 14, 2022, and March 28, 2022. $News^{AHT}_{i,t}$ is a dummy variable when there is firm-specific news announced during AHT, and no news announced or daily neutral news sentiment during RTH from RavenPack. We include time (Weekday) and firm fixed effects in the specification.

[Table VI about here.]

In Table VI, we report the results of the DiD analysis around the Robinhood AHT extension. We first note that both the buyer and seller-initiated odd-lot trades in the second

[16] In Internet Appendix Section C, we show the results of two-way fixed effects regressions for different types of news.

half (from 06:00 pm to 08:00 p.m. EST) of AHT relative to the first half (from 04:00 pm to 06:00 p.m. EST) increase significantly on CBOE and NYSE while we see a significant decline on NASDAQ. Firm-specific news are often released in the first half of AHT, so we see a significant decline only in buyer-initiated odd-lot trades on CBOE in the second half of trading. The coefficient of the interaction term, β_3 reveals that news triggers AHT both buyer and seller-initiated odd-lot trades on CBOE once retailers can trade longer hours on the Robinhood platform. We see a similar increase only in buyer-initiated odd-lots on NYSE conditional on news, while seller-initiated odd-lots in the second half decline on the days of news releases. Overall, these results are in line with the view that CBOE odd-lot trades are a good proxy for retail participation in AHT on firm-specific news days.

IV. AHT Liquidity Provision

For retail traders, who are constrained to provide liquidity during AHT, the question is whether event-driven market participation in a volatile environment is the right choice. Although faster access to public information is crucial, the question remains whether retail traders benefit from retail priority in liquidity provision when more sophisticated traders can exploit low-latency technology to react to public news.

A. Introduction of CBOE Retail Priority

We first look at the profits to liquidity provision around the introduction of the retail priority rule on the CBOE EDGX platform, on November 1, 2019. Most limit order books (LOBs) follow price-time precedence rules, that is, best prices (the highest bid and the lowest ask) get the first execution. If both quotes are submitted at the same price, the first quote that arrives at the LOB gets the first execution. The novel feature introduced by the CBOE EDGX platform allows retail traders to jump the queue, that is, the price-retail-time priority. This feature levels the playing field for retail traders against traders with low-latency

technologies. However, at the same time it poses the danger of exposing retail traders to picking-off risk around news arrivals unless retailers constantly monitor the market and have the capacity of fast cancellations in case of unexpected price moves (Khomyn and Putniņš, 2021; Copeland and Galai, 1983).

We use a DiD setting to test the interaction between the introduction of the retail priority rule on the CBOE EDGX platform and AHT news releases and its effect on the profits to liquidity provision measured by the realized spreads around buyer-and seller-initiated odd-lot trades on different venues. We estimate the following DiD regression using a 60-day window around the AHT introduction date on the CBOE EDGX platform:

$$y_{i,t} = \alpha_i + \gamma_t + \beta_1 RP^{EDGX}_{t,int} + \beta_2 earnings^{AHT}_{i,t} + \beta_3 RP^{EDGX}_{t,int} \times earnings^{AHT}_{i,t} + \epsilon_{i,t} \qquad (4)$$

The dependent variable $y_{i,t}$ is the average realized spread around the buyer-initiated (Panel A) and seller-initiated (Panel B) odd-lot trades from 04:00 pm to 08:00 p.m. EST of stock i on the day t (as well as trades at each venue, i.e., CBOE, FINRA, NASDAQ, and NYSE). $RP^{EDGX}_{t,int}$ is a dummy variable equal to one for days between November 1, 2019, and December 16, 2019, and zero for days between September 20, 2019, and October 31, 2019. $Earnings^{AHT}_{i,t}$ is a dummy variable when there is firm-specific earnings news announced during AHT, and no news announced or daily neutral news sentiment during RTH from RavenPack. We include time (Weekday) and firm fixed effects in the specification.

[Table VII about here.]

We report the results in Table VII. We focus on the interaction term showing the effect of the introduction of retail priority on CBOE EDGX platform on profits to liquidity provision on days with AHT earnings news. We see that there is a significant reduction in realized spreads only on the CBOE EDGX platform providing compelling evidence on the adverse effect of retail priority on liquidity providers. When we split the sample based on the AHT

return volatility measured by absolute return, we note in Panel B that the effect mainly comes from stocks with high AHT return volatility, indicating picking-off risk for stale retail limit orders on days of uncertain earnings news.

B. A Tale of Two Events

We next provide microscopic evidence on intraday AHT liquidity provision around two events: i) Apple's (AAPL) earnings news on July 30, 2020, at 04:30 pm EST that attracted the highest Robinhood popularity on an earnings announcement day in the Robintrack sample.[17] and ii) Gamestop (GME) frenzy on January 26, 2021, triggered by Elon Musk's tweet "GameStonk" at 04:08 pm EST. This analysis allows us to compare the reaction of market participants on different exchanges to unscheduled and scheduled events.

B.1. Apple's Earnings News

Apple's AHT earnings news above analysts' expectations on July 30, 2020, resulted in a large price increase (around 6%) in after-hours trading (Fortune.com, 2020). While there were several earnings news during AHT on that day, e.g., revenues, earnings per share, sales, etc., the first AHT news appeared on Dow Jones newswires at 04:30:00 pm EST. This news which we take as the main news event triggered an initial price increase of around 3.8% within a 5-minute window (see Panel A of Figure 7).

[Figure 7 about here.]

Figure 7 shows the quote updates on different exchanges around Apple's earnings news on July 30, 2020. We report the number of quote updates within 30-second intervals that improve the best (ask and bid) price and the number of quote updates that increase the BBO depth both at the best bid and ask levels, reflecting aggressive liquidity provision. Quotes, especially odd-lot quotes, play an important role in the price discovery process (Bartlett

[17] When we include only the news that is released after 04:10 pm EST to allow sufficient time for the pre-event window.

et al., 2025; Gregoire and Martineau, 2022). We also report the average transaction price and the number of trades initiated on each exchange within 30-second intervals.

We first notice "the calm before the storm" effect without much fluctuation in price or trading activity before the release of the earnings news. We also detect the rapid reaction to the news, with the highest increase in the quote and trades on NASDAQ, with ask prices driving the post-event price suggesting that NASDAQ drives the price discovery process followed by market participants on other exchanges.[18] In other words, on the news days when retail traders are active, there are sophisticated traders with low-latency technology.

B.2. GameStop Tweet

The GameStock saga which started in January 2021 took a new turn when Elon Musk tweeted at 04:08pm EST on January 26, 2021, with a link to a bullish view on Reddit's Wallstreetbets which triggered a price rally and subsequent short-squeeze (Reuters, 2021). This is an example of unscheduled AHT news that moved after-hours trading. A microscopic view of trading around the tweet reveals some interesting similarities and differences compared to the previous example of scheduled news.

[Figure 8 about here.]

Figure 8 shows the quote updates on different exchanges around Elon Musk's tweet. We report the number of quote updates within 30-second intervals that improve the best (ask and bid) price and the number of quote updates that increase the BBO depth both at the best bid and ask levels. We also report the average transaction price and the number of trades initiated on each exchange within 30-second intervals.

Although the tweet initially generated a modest quote reaction but a jump in trades with a temporary price move, after-hours trading became active only a few minutes later.

[18] These observations are not unique to the Apple's example. In online Appendix D, we show the average results for 56 positive earnings news events of ten S&P 500 stocks followed by retail traders based on Robinhood popularity. The patterns are very similar.

As in the previous case, the price rally is mainly driven by quote updates on NASDAQ. Both examples suggest that traders on NASDAQ have a speed advantage which exposes the liquidity providers on other exchanges to adverse selection risk (Biais et al., 2015; Foucault et al., 2016; Colliard et al., 2022).

V. Conclusion

This paper documents new evidence on the microstructure of the after-hours market on U.S. trading venues. We compare the trading activity and market liquidity of both RTH and AHT over a long time series and document important differences. Although trading activity in AHT is generally only a fraction of the RTH activity, AHT is elevated on days with firm-specific news. Earlier papers suggest that AHT activity mainly concentrates on scheduled corporate event days, such as earning announcements. We confirm that this is still true, however, this captures only a tiny fraction of the bigger picture. Our analysis reveals that the landscape of AHT has changed substantially, especially in the last few years with the entry of zero-commission platforms such as Robinhood, which facilitate retail trading in the after-hours market. Robinhood platform gradually increased the scope of AHT, initially offering the service to all its customers until 06:00 pm EST in 2018 and extending the hours until 08:00pm EST in 2022. We exploit these changes to identify the type of news that attracts ATH (retail) trading.

We collect news for a broad set of corporate events that occur after markets close, including both scheduled and unscheduled news events. We show that scheduled firm-specific news, which is predominantly positive, is an important trigger for AHT. While after-hours markets play a crucial role in revealing insider information as the most common AHT news type, we do not find strong evidence that retailers chase insider news.

Using machine-learning techniques, we identify buyer-initiated odd-lot trades, especially those originating from the CBOE EDGX platform as the main indicator of AHT retail

activity. Note that CBOE EDGX platform offers retail priority to its customers, meaning retail orders at the best price have precedence over orders that arrive earlier at the same price. Although this priority is valuable for liquidity providers in the event of competition for liquidity provision, our intraday analysis suggests that it potentially exposes retail traders (on CBOE EDGX) to picking off risk by sophisticated traders (on NASDAQ), especially on days with news releases. We need more granular data to understand the severity of the problem, particularly how sophisticated traders exploit their ability to monitor the market and their speed advantage in after-hours markets.

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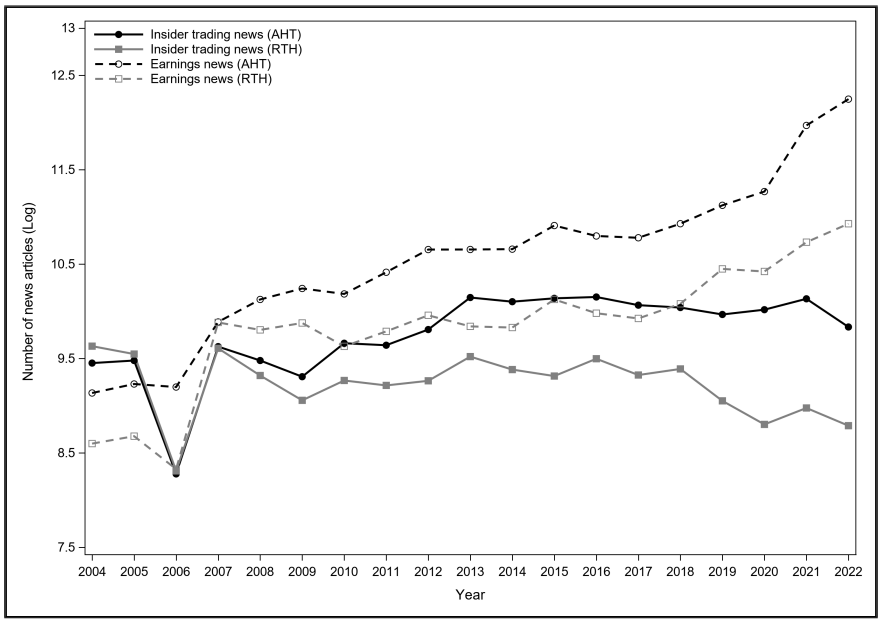
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Figure 1. News over Time

The figure plots the number of news (from RavenPack) of *scheduled* earnings news and *unscheduled* insider trading news published during AHT and RTH per year for S&P 1500 stocks. Panel A reports the natural logarithm of the total number of news articles per year. Panel B reports the natural logarithm of the total number of news events (a news event can be reproduced and disseminated through many news articles). The sample period is from January 5, 2004 to October 31, 2022. Regular trading hours (RTH) refers to trading session during 09:30 a.m. to 04:00 p.m. EST. After-hours trading (AHT) refers to the trading session from 04:00 p.m. to 08:00 p.m. EST.

(a) News articles



(b) News events

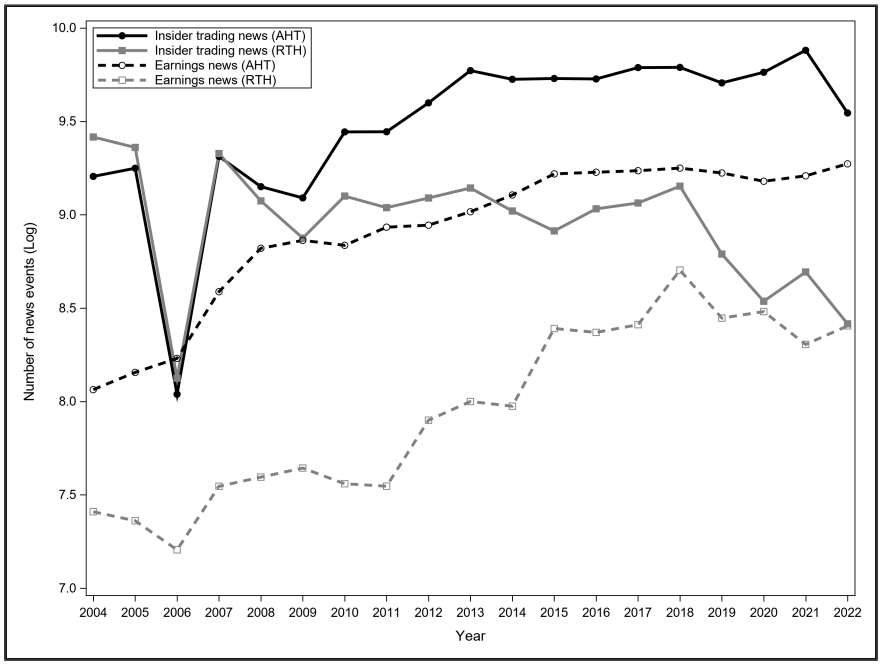
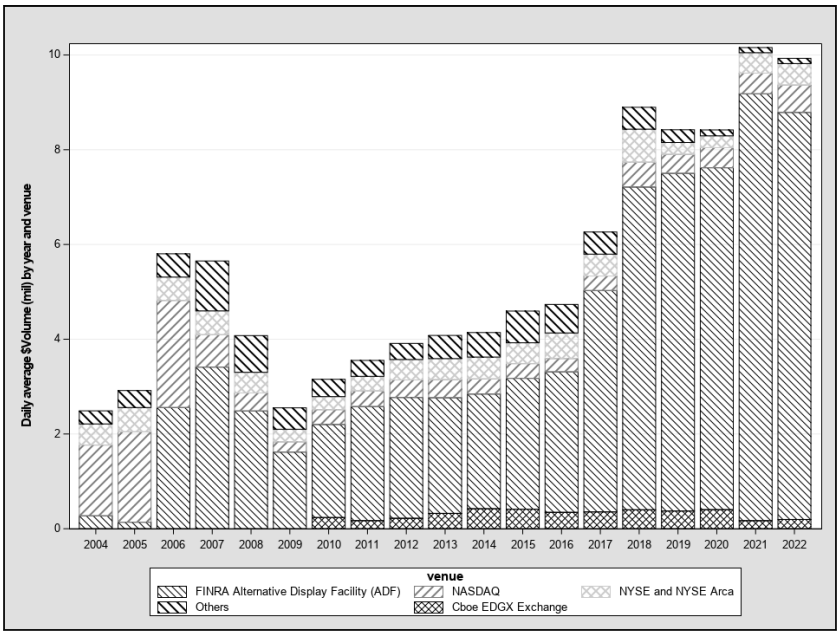


Figure 2. Trading venue over time

The figure plots the time series of the daily average number of trades and dollar trading volume for S&P 1500 stocks in the after-hours market, during the period January 5, 2004, to October 31, 2022. The daily average number of trades and dollar volume (in millions) is the average across all stocks and different trading platforms over a year. The trading venues include the CBOE EDGX Exchange, platforms that report FINRA alternative display facility (ADF), NASDAQ, NYSE, and other smaller trading platforms.

(a) Dollar trading volume by venue and year



(b) Number of trades by venue and year

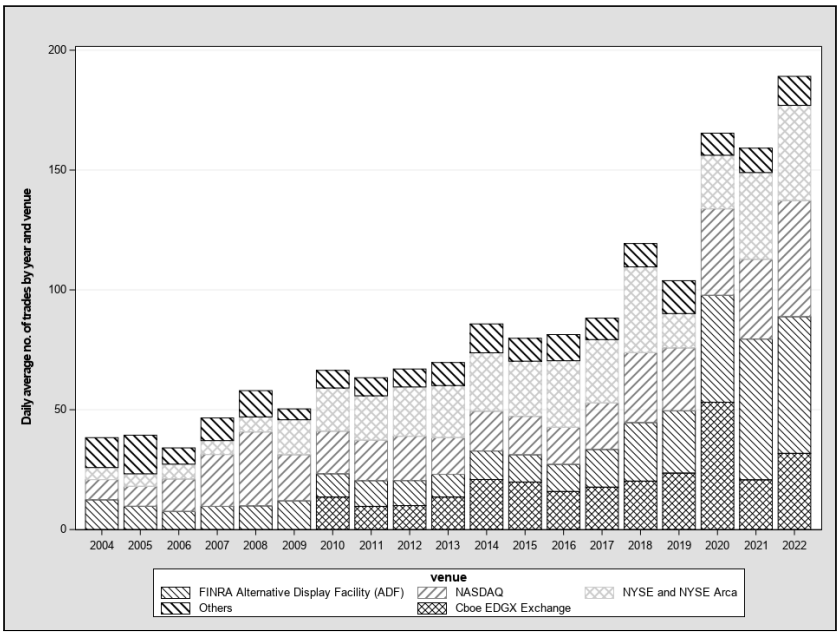
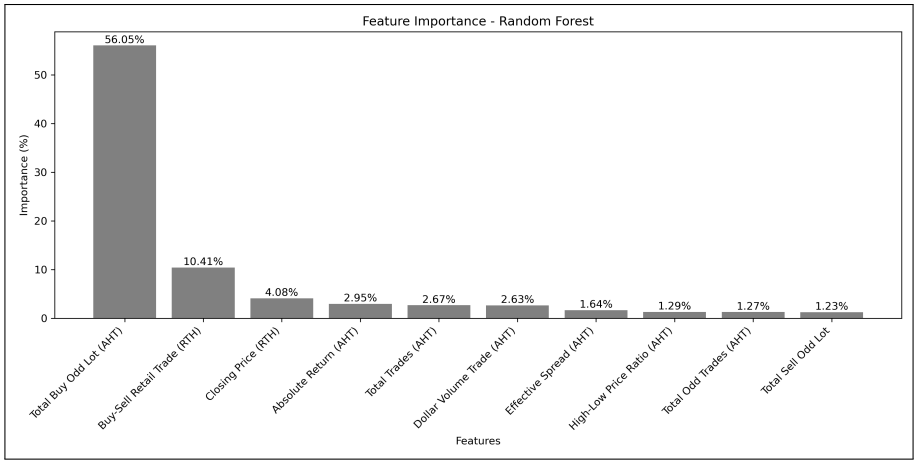


Figure 3. Feature Importance

This figure ranks features by their importance according to Random Forest's internal procedure that ranks features based on the total reduction in Gini impurity (a default option that aggregates the importance of each feature across all splits where the feature was used). The target variable is the absolute value of the difference in the number of users holding S&P 1500 constituents on Robinhood for each day between 04:00 p.m. and 08:00 p.m. In Panel B, the trading venues include CBOE EDGX Exchange, platforms that report to FINRA alternative display facility (ADF), NASDAQ, NYSE (ARCA), and other smaller trading platforms. The sample period is from May 3, 2018, to May 27, 2020. We include 37 (41) explanatory variables, i.e., features, in Panel A (Panel B). They are defined in Internet Appendix Table A.1.

(a) Feature Importance



(b) Feature Importance - By Venue

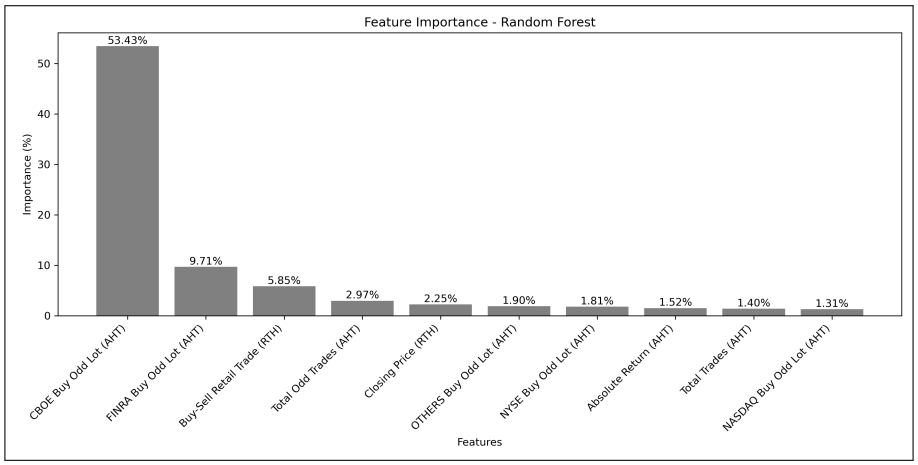


Figure 4. Robinhood Popularity Forecast

This figure shows the out-of-sample predicted and actual values of the absolute value of the difference in the number of users holding S&P 1500 constituents on the Robinhood platform for each day between 04:00 p.m. and 08:00 p.m. We use the random forest algorithm and split our initial sample period (from May 3, 2018 to May 27, 2020) as training (80%) and test sample (20%). We use the remaining 10% of the Robintrack data, from May 28, 2020 to August 13, 2020 as the out-of-sample period. The shaded areas show the rolling 99% confidence interval. The list of predictors is in Internet Appendix Table A.1.

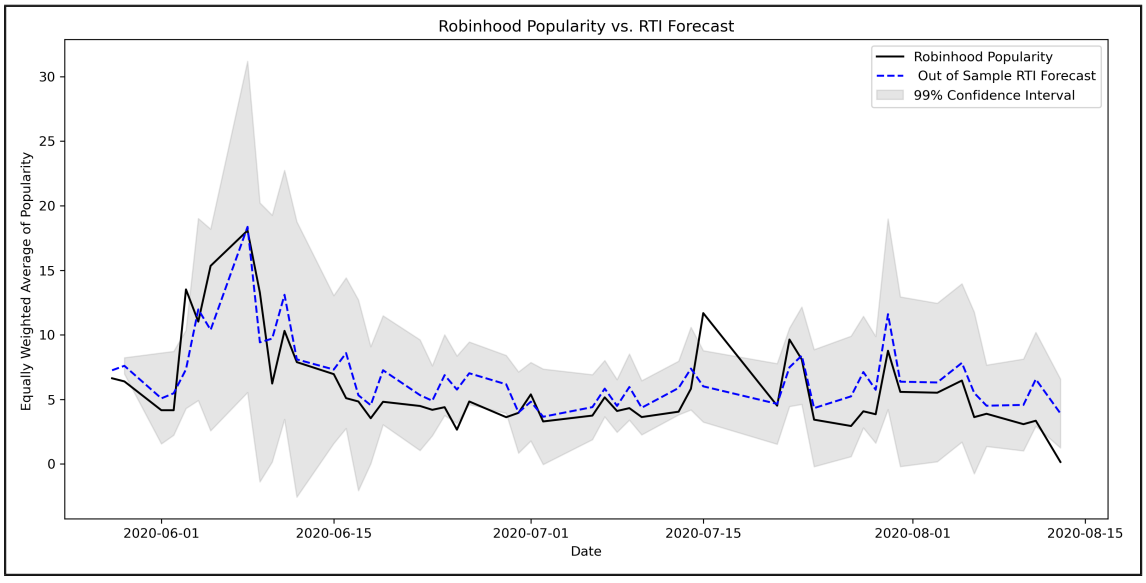
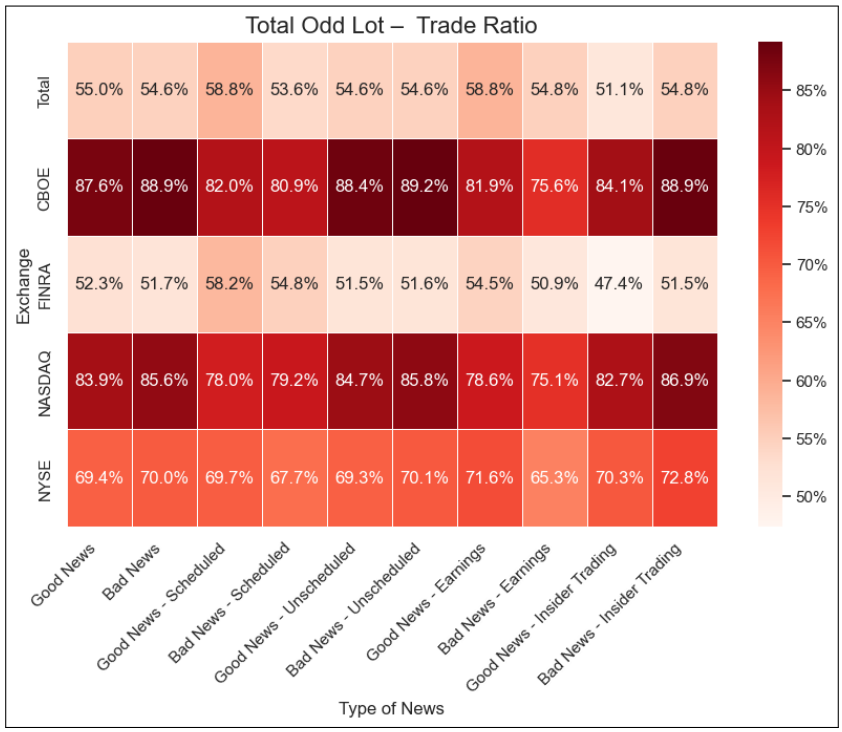


Figure 5. Odd-lot Trades

This figure shows the ratio AHT odd-lot trades to the total number of trades across venues. Panel A shows the heatmap of the value-weighted average of the odd-lot to total trade ratio across venues and different types of news over the sample from August 1, 2018, to October 31, 2022. Panel B shows how the odd-lot to total trade ratio evolves. The shaded area indicates the Covid-19 period, from February 3, 2020 to September 29, 2020. The trading venues include the CBOE EDGX Exchange, platforms that report FINRA alternative display facility (ADF), NASDAQ and NYSE.

(a) Heatmap



(b) Odd-lot to Total Trade over Time

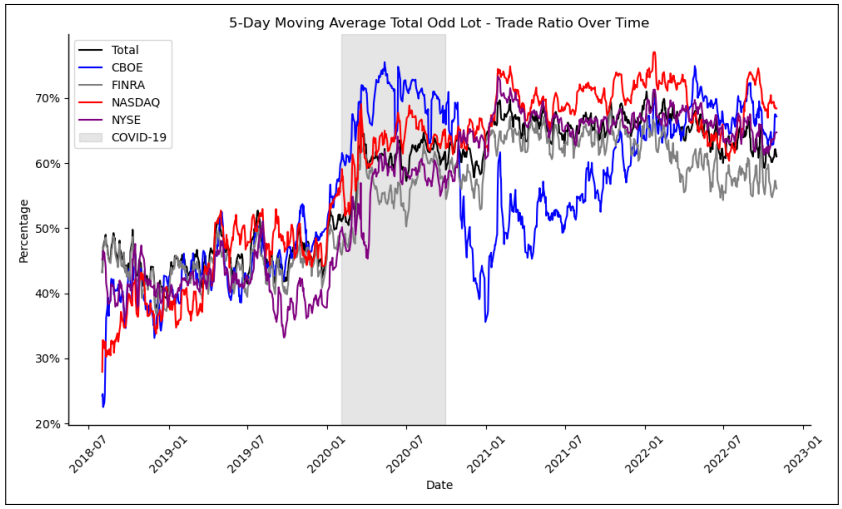


Figure 6. News Days

This figure shows the results of the two-way fixed effects model (Equation 4) around news days. The sample covers from August 1, 2018, to October 31, 2022. The trading venues include the CBOE EDGX Exchange, platforms that report FINRA alternative display facility (ADF), NASDAQ, NYSE and other smaller exchanges.

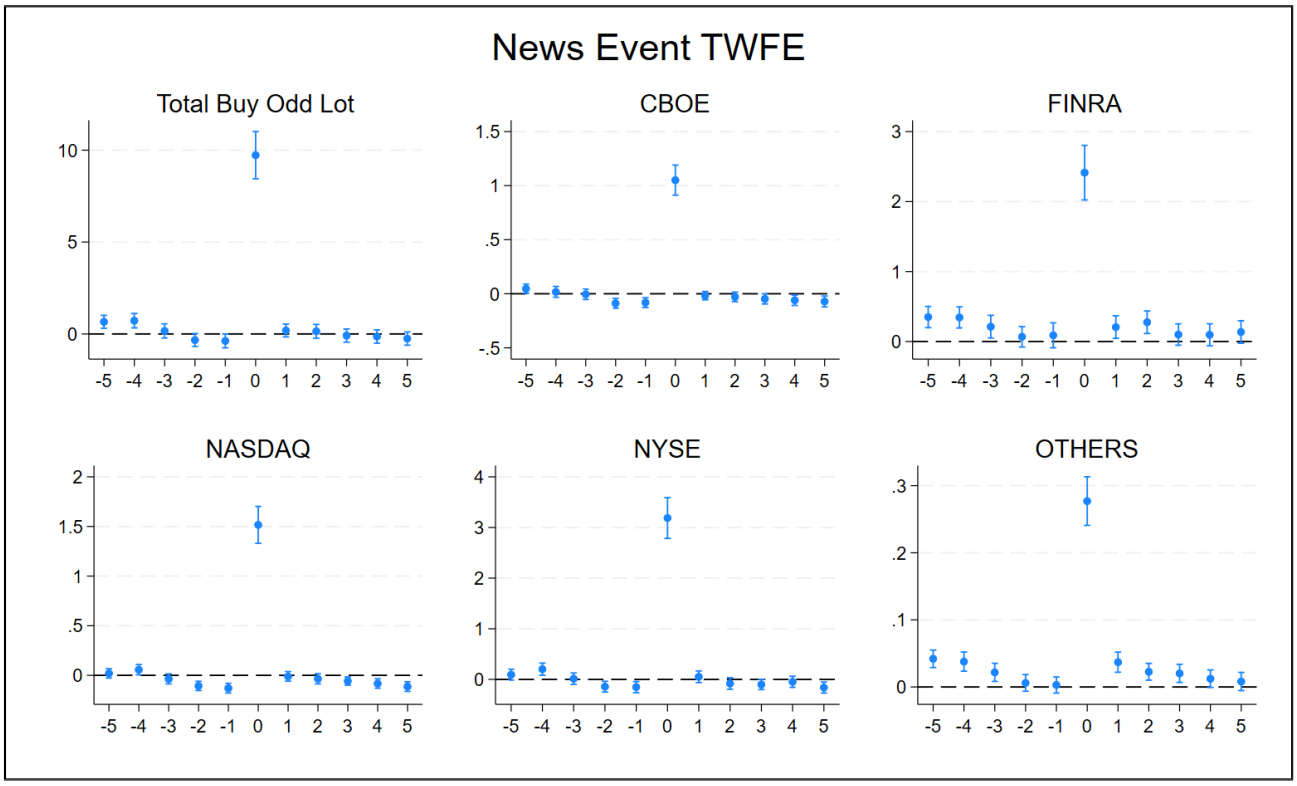
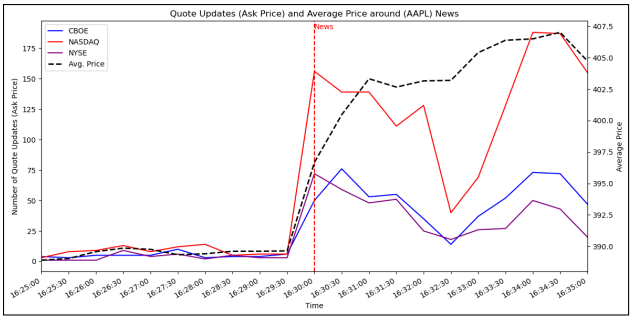


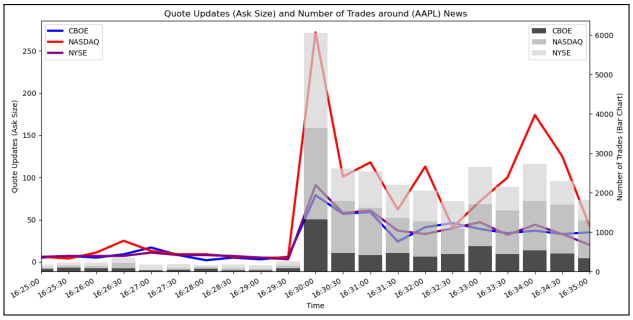
Figure 7. Apple Earnings News

This figure shows the quote updates on different exchanges around Apple's earnings news on July 30, 2020. We report the number of quote updates within 30-second intervals that improve the best (ask and bid) price and the number of quote updates that increase the BBO depth both at the best bid and ask levels. We also report the average transaction price and the number of trades initiated on each exchange within 30-second intervals. The event occured at 04:30 pm EST when the first news was released on Dow Jones newswires. The pre-event (post) event window is five minutes sampled at a 30-second frequency. The exchanges include the CBOE EDGX, NASDAQ, and NYSE.

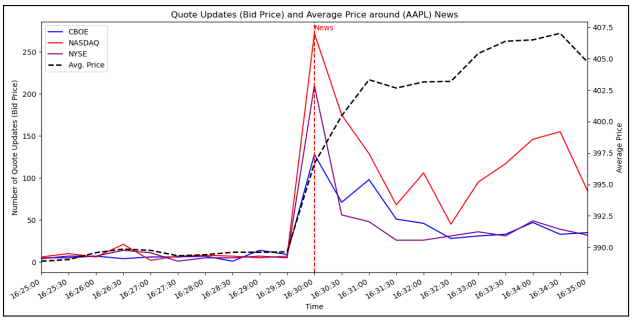
(a) Ask Price



(b) Ask Size



(c) Bid Price



(d) Bid Price

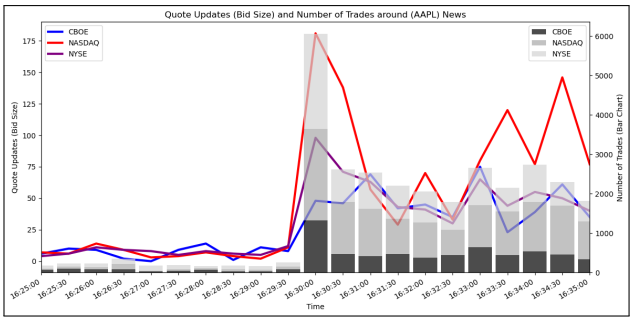
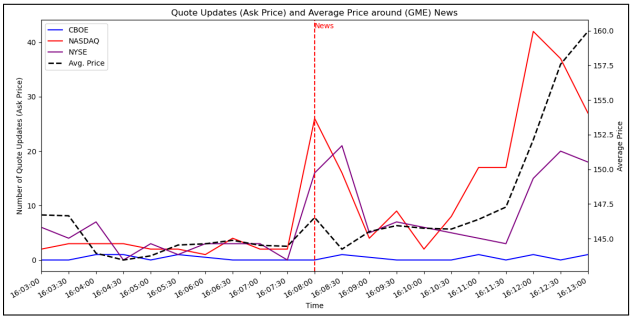


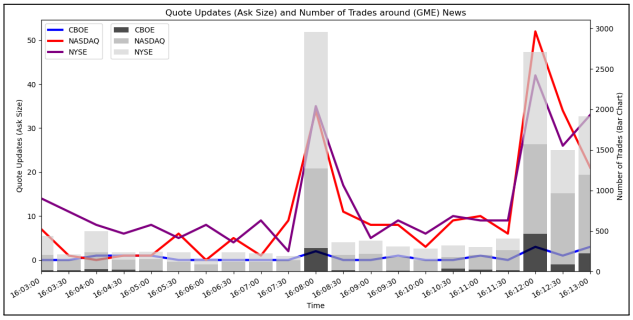
Figure 8. GameStop Tweet

This figure shows the quote updates on different exchanges around Elon Musk's tweet on January 26, 2021. We report the number of quote updates within 30-second intervals that improve the best (ask and bid) price and the number of quote updates that increase the BBO depth both at the best bid and ask levels. We also report the average transaction price and the number of trades initiated on each exchange within 30-second intervals. The event occurred at 04:08 pm EST when Elon Musk tweeted "GameStonk". The pre-event (post) event window is five minutes sampled at a 30-second frequency. The exchanges include the CBOE EDGX, NASDAQ, and NYSE.

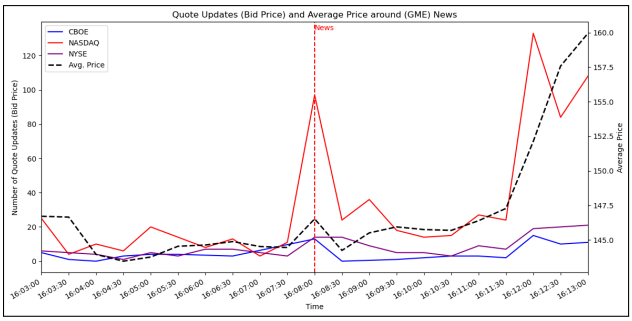
(a) Ask Price



(b) Ask Size



(c) Bid Price



(d) Bid Price

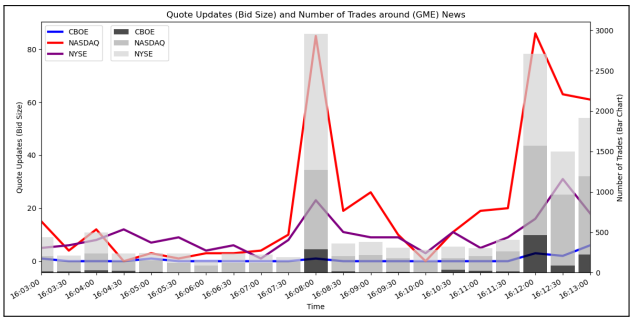


Table I Summary statistics

The table presents the trading activity (e.g., number of trades and dollar volume) and liquidity measures (e.g., bid-ask spread and its components) for S&P 1500 stocks from January 5, 2004, to October 31, 2022. All statistics are equal-weighted averages across stocks in Panel A and value-weighted averages in Panel B, using market capitalization at the end of the previous year. Spreads are measured in basis points. Regular trading hours (RTH) refer to trading sessions from 09:30 a.m. to 04:00 p.m. EST. After-hours trading (AHT) refers to trading sessions from 04:00 p.m. to 08:00 p.m. EST.

Panel A. Equally-Weighted Average							
Panel A.1. RTH	Mean	Std. Dev.	P5	P25	Median	P75	P95
Trade (thousands)	10.85	17.82	0.48	1.70	4.45	12.13	42.00
$Volume (millions)	90.08	198.30	1.48	7.22	23.51	82.39	386.53
Quoted spread	14.16	14.72	1.48	5.25	9.48	17.57	40.67
Effective spread	12.17	13.65	2.48	4.69	7.95	14.17	35.21
Realized spread	3.43	9.43	-4.66	-0.35	1.78	5.13	17.72
Price impact	8.75	12.01	-0.90	2.66	5.60	10.97	28.88
Panel A.2. AHT	Mean	Std. Dev.	P5	P25	Median	P75	P95
Trade	24.26	68.36	2.00	5.00	10.00	19.00	68.00
$Volume (millions)	3.50	10.94	0.02	0.13	0.47	1.99	15.53
Quoted spread	503.68	518.85	22.07	126.37	345.72	684.24	1,651.40
Effective spread	175.69	267.30	7.51	30.15	75.06	195.05	725.04
Realized spread	147.22	271.85	-14.54	16.20	54.68	162.30	692.01
Price impact	11.16	112.52	-77.50	-0.95	0.00	10.06	143.53
Panel B. Value-Weighted Average							
Panel B.1. RTH	Mean	Std. Dev.	P5	P25	Median	P75	P95
Trade (thousands)	47.09	43.21	2.83	12.90	31.10	69.78	135.05
$Volume (millions)	596.93	565.75	20.63	135.15	378.91	928.17	1,666.76
Quoted spread	4.89	5.61	1.54	2.18	3.31	5.36	13.42
Effective spread	5.13	5.99	1.51	2.35	3.57	5.74	13.31
Realized spread	1.88	5.48	-3.05	-0.21	1.14	2.94	8.94
Price impact	3.25	5.69	-1.86	0.95	2.41	4.43	10.98
Panel B.2. AHT	Mean	Std. Dev.	P5	P25	Median	P75	P95
Trade	153.43	235.25	6.00	17.00	41.00	139.00	736.00
$Volume (millions)	27.30	34.53	0.27	2.58	10.22	38.27	101.78
Quoted spread	162.62	253.24	6.08	21.51	62.48	197.34	633.41
Effective spread	71.17	120.15	5.70	16.51	34.22	74.59	256.42
Realized spread	54.47	116.33	-6.68	8.45	24.47	59.41	217.79
Price impact	5.60	55.25	-28.14	-1.00	0.32	6.80	56.47

Table II List of News

The table lists the twenty-two news categories covered by Ravenpack for S&P 1500 stocks, during the period January 5, 2004 to October 31, 2022. The number of news (*News*) articles counts all the news stories covered by RavenPack and the number of new events (*Events*) covers the number of first news articles reporting a categorized event about the specific firm. We report the fraction of scheduled (*Scheduled*) news as identified by Ravenpack. We also report the ratio of bad over good news (*B/G*). We define Good News (Bad News) if the accumulated adjusted RavenPack news sentiment scores from 4:00 p.m. to 8:00 p.m. EST take a value of 50 to 100 (0 to 50). A score of 50 represents a neutral sentiment. Regular trading hours (RTH) refers to trading sessions from 09.30 a.m. to 04.00 p.m. EST. After-hours trading (AHT) refers to the trading session from 04:00 p.m. to 08:00 p.m. EST.

	AHT					RTH					All				
News Group	Events	Freq	Scheduled	B/G	News	Events	Freq	Scheduled	B/G	News	Events	Freq	Scheduled	B/G	News
Analyst Ratings	31,403	2.33%	0.00%	0.43	39,021	125,298	5.29%	0.00%	0.49	197,589	156,701	4.22%	0.00%	0.48	236,610
Assets	15,215	1.13%	6.81%	0.28	58,419	29,266	1.24%	7.65%	0.23	113,156	44,481	1.20%	7.36%	0.25	171,575
Corp. Resp.	1,154	0.09%	0.00%		5,139	2,483	0.10%	0.00%		12,302	3,637	0.10%	0.00%		17,441
Credit	7,774	0.58%	0.04%	0.22	54,067	7,277	0.31%	0.03%	0.19	33,595	15,051	0.41%	0.03%	0.20	87,662
Credit Ratings	16,863	1.25%	0.00%	0.77	54,056	41,238	1.74%	0.00%	0.64	120,105	58,101	1.56%	0.00%	0.68	174,161
Dividends	32,378	2.40%	97.02%	0.07	199,424	27,317	1.15%	96.11%	0.04	140,505	59,695	1.61%	96.60%	0.06	339,929
Earnings	310,031	23.02%	93.12%	0.34	1,290,085	116,402	4.92%	96.26%	0.53	528,833	426,433	11.48%	93.98%	0.38	1,818,918
Equity Actions	59,704	4.43%	5.79%	1.25	133,553	155,179	6.55%	1.70%	1.36	247,522	214,883	5.79%	2.84%	1.33	381,075
Indexes	918	0.07%	0.00%	0.13	4,956	196	0.01%	0.00%	0.20	754	1,114	0.03%	0.00%	0.14	5,710
Insider Trading	361,642	26.86%	0.00%	2.62	495,202	257,210	10.86%	0.00%	2.29	337,215	618,852	16.66%	0.00%	2.49	832,417
Investor Relations	27,537	2.04%	97.58%		199,043	41,601	1.76%	97.30%		192,269	69,138	1.86%	97.41%		391,312
Labor Issues	62,028	4.61%	0.00%	0.41	319,757	77,840	3.29%	0.00%	0.32	385,746	139,868	3.77%	0.00%	0.36	705,503
Legal	17,691	1.31%	8.68%	3.75	129,746	30,264	1.28%	9.36%	4.02	211,578	47,955	1.29%	9.11%	3.92	341,324
Marketing	30,884	2.29%	96.99%	0.02	204,126	42,413	1.79%	94.55%	0.02	185,913	73,297	1.97%	95.58%	0.02	390,039
M&A	56,739	4.21%	10.15%	0.75	224,825	140,814	5.95%	5.49%	0.40	412,661	197,553	5.32%	6.83%	0.49	637,486
Order Imbalances	6,629	0.49%	0.00%	0.76	8,778	322,260	13.61%	0.00%	0.84	424,479	328,889	8.86%	0.00%	0.84	433,257
Partnerships	12,049	0.89%	0.00%	0.03	64,453	35,374	1.49%	0.00%	0.01	209,630	47,423	1.28%	0.00%	0.02	274,083
Price Targets	9,757	0.72%	0.00%	0.58	11,786	63,578	2.69%	0.00%	0.60	108,211	73,335	1.97%	0.00%	0.60	119,997
Products Services	52,234	3.88%	27.24%	0.12	307,683	123,248	5.21%	36.48%	0.10	751,626	175,482	4.72%	33.73%	0.11	1,059,309
Revenues	109,480	8.13%	73.29%	0.36	232,675	30,321	1.28%	77.16%	0.47	105,326	139,801	3.76%	74.13%	0.39	338,001
Stock Prices	100,070	7.43%	0.00%	0.82	252,432	219,680	9.28%	0.00%	0.84	511,890	319,750	8.61%	0.00%	0.83	764,322
Technical Analysis	24,395	1.81%	0.00%	0.84	27,572	478,149	20.20%	0.00%	0.86	520,906	502,544	13.53%	0.00%	0.86	548,478
Total	1,346,575	100%		0.83	4,316,798	2,367,408	100%		0.72	5,751,811	3,713,983	100%		0.76	10,068,609

Table III News and AHT

This table presents the results for trades, dollar volume, quoted Spread, effective spread, realized spread, and the price impact of trades across two sub-samples. Panel A covers the period from January 5, 2004, to July 31, 2018, while Panel B covers the period from August 1, 2018, to October 31, 2022. The variable News is a dummy variable, equal to 1 if a news event is announced during after-hours trading (AHT), and 0 if no news is announced or if neutral sentiment news is reported during regular trading hours (RTH). We define Good News (Bad News) if the accumulated adjusted RavenPack news sentiment scores from 4:00 p.m. to 8:00 p.m. take a value of 50 to 100 (0 to 50). News (RTH) is defined as if a news event is announced during regular-hour trading (RTH), and 0 if no news is announced or if neutral sentiment news is reported during after-hour trading (AHT). We use RavenPack's classification to distinguish between scheduled and unscheduled news events and exclude days with overlapping scheduled and unscheduled news in case of unscheduled news. Earnings data only includes scheduled earnings announcements (group and type are equal to earnings, "Ravenpack Definition"). For insider trading, we only use it if there is insider-buy or insider-sell news, we exclude the days if there is insider-buy and insider-sell news on the same day. All variables are winsorized at the 0.05% and 99.5% levels to reduce the influence of extreme values. Spreads are measured in basis points. The reported statistics are value-weighted across stocks using market capitalization at the end of the previous year.

Panel A: Pre-2018	Total	News	No-News	Good	Bad	RTH	Scheduled	Unscheduled	Earnings	Insider Trading
Trade	71.47	74.05	36.19	82.23	63.74	71.43	156.46	61.21	253.35	52.32
$Volume (millions)	17.31	17.49	9.95	18.86	15.76	19.41	22.58	16.69	24.21	13.30
Quoted spread	169.98	153.45	187.00	144.75	164.45	128.11	142.40	155.21	179.23	189.54
Effective spread	72.45	72.45	77.30	71.67	73.44	64.66	96.64	68.58	149.11	77.77
Realized spread	55.15	53.72	57.55	52.56	55.19	48.95	71.01	50.96	107.38	60.29
Price impact	5.47	5.88	5.35	6.12	5.89	5.35	12.52	4.82	23.39	5.12
Panel B: Post-2018	Total	News	No-News	Good	Bad	RTH	Scheduled	Unscheduled	Earnings	Insider Trading
Trade	281.13	222.60	114.38	230.29	213.22	330.36	341.36	211.47	376.88	188.26
$Volume (millions)	42.85	35.04	21.38	36.11	33.74	49.64	43.89	34.21	38.52	32.16
Quoted spread	119.19	112.67	162.13	109.08	117.04	77.43	110.76	112.85	156.03	133.12
Effective spread	59.01	63.10	72.65	63.37	62.76	47.49	83.84	61.15	134.99	63.84
Realized spread	48.58	50.80	58.85	50.53	51.13	37.37	65.08	49.46	105.63	52.27
Price impact	7.15	9.74	8.12	10.25	9.12	6.95	14.35	9.31	22.80	8.02

Table IV Market Reaction to AHT News Sentiment

The table contains the results of average AHT trading activities and next trading day returns based on AHT news sentiment. At the end of each trading day t, we construct equally-weighted average raw return during AHT, R_t^{AHT}, its absolute value of $|R_t^{AHT}|$, as well as the equally weighted average next-day adjusted return based on Fama-French 6 portfolios formed on size and book-to-market (2X3) return $R_{FF,t+1}^{RTH}$. We conduct a two-sided t-test to evaluate the significance of the difference between days after-hour news sentiment and no-news baseline. We define *Good News* (*Bad News*) if the adjusted RavenPack news sentiment scores from 04:00 p.m. to 08:00 p.m. EST take the value 50 to 100 (0 to 50). A score of 50 represents a neutral sentiment. *No News* refers to no news announcements or neutral news in AHT and the next trading day's RTH. The pre-2018 period (Panel A) is from January 5, 2004, to July 31, 2018. The post-2018 period (Panel B) is from August 1, 2018, to October 31, 2022. *,** and *** indicate significance at the 10%, 5% and 1% levels, respectively. Regular trading hours (RTH) refers to trading session during 09:30 a.m. to 04:00 p.m. EST. After-hours trading (AHT) refers to the trading session from 04:00 p.m. to 08:00 p.m. EST.

Type of News	Panel A: Pre-2018			Panel B: Post-2018		
	$\lvert R_t^{AHT}\rvert$	R_t^{AHT}	$R_{FF,t+1}^{RTH}$	$\lvert R_t^{AHT}\rvert$	R_t^{AHT}	$R_{FF,t+1}^{RTH}$
News	0.190***	-0.005	0.036***	0.087***	0.015***	-0.000
	(57.519)	(-1.436)	(6.278)	(28.888)	(4.633)	(-0.066)
Good News	0.259***	0.079***	0.246***	0.103***	0.052***	0.139***
	(54.997)	(16.007)	(28.071)	(23.416)	(11.251)	(14.086)
Bad News	0.120***	-0.088***	-0.173***	0.072***	-0.023***	-0.144***
	(26.348)	(-18.898)	(-23.526)	(18.048)	(-5.574)	(-15.053)
Good News - Scheduled	1.005***	0.194***	0.584***	1.027***	0.338***	0.464***
	(58.955)	(10.394)	(19.007)	(32.550)	(9.876)	(8.861)
Bad News - Scheduled	1.615***	-1.069***	-1.307***	1.398***	-1.059***	-1.465***
	(35.521)	(-21.965)	(-17.523)	(17.425)	(-12.694)	(-12.694)
Good News - Unscheduled	0.182***	0.092***	0.225***	0.129***	0.117***	0.237***
	(37.887)	(18.428)	(26.493)	(26.679)	(18.559)	(20.591)
Bad News - Unscheduled	0.104***	-0.083***	-0.158***	0.129***	-0.078***	-0.216***
	(22.881)	(-17.937)	(-22.556)	(22.729)	(-13.234)	(-20.180)
Good News - Earnings	1.716***	0.400***	1.044***	0.779***	0.259***	0.325***
	(53.429)	(10.882)	(18.072)	(18.091)	(5.526)	(3.916)
Bad News - Earnings	2.092***	-1.186***	-1.320***	1.105***	-0.694***	-1.299***
	(37.037)	(-18.867)	(-13.038)	(12.311)	(-7.157)	(-7.935)
Good News - Insider trading	0.046***	0.019***	0.349***	0.118***	0.073***	0.416***
	(7.831)	(3.144)	(23.017)	(12.093)	(7.090)	(14.850)
Bad News - Insider trading	-0.028***	-0.005**	-0.101***	0.021***	-0.020***	-0.208***
	(-11.290)	(-1.998)	(-15.746)	(4.176)	(-3.840)	(-16.364)

Table V DiD Analysis: News and Robinhood Popularity

This table reports the results of the difference-in-difference regressions on the panel for all S&P 1500 stocks on each day. Panel A (Panel B) shows the results for Robinhood investor popularity (the number of trades as the dependent variable. Robinhood Popularity is defined as the absolute change in the number of users holding a stock in the Robintrack data between 04:00 pm and 08:00 pm. We use the first observation between 04:00 pm and 05:00 pm and the last observation between 07:00 pm and 08:00 pm. If data is missing between 07:00 pm and 08:00 pm, we calculate the difference using the last available data point between 06:00 pm and 07:00 pm. If this is also missing, we use the last data point between 05:00 pm and 06:00 pm. RH_t^{AHT} is a dummy variable equal to one for days between August 1, 2018 and September 13, 2018, and zero for days between June 18, 2018 and July 31, 2018. $News_{i,t}^{AHT}$ is a dummy variable set to 1 if a news event is announced during after-hours trading (AHT), and to 0 if no news is announced or if only neutral-sentiment news is reported during regular trading hours (RTH). Good News (Bad News) is defined when the accumulated adjusted RavenPack news sentiment score between 04:00 pm and 08:00 pm take the value between 50 and 100 (0 and 50). We use RavenPack's classifications to distinguish between scheduled and unscheduled news events, excluding days with overlapping scheduled and unscheduled news in the analysis of unscheduled news. *No News* refers to no news announcements or having accumulated neutral news in AHT and RTH. $News_{i,t}^{AHT}$ *X* RH_t^{AHT} is the interaction variable of $News_{i,t}^{AHT}$ and RH_t^{AHT}. Weekday and firm fixed effects are included. T-statistics (in parentheses) are based on standard errors clustered at the firm level. ***,**, and * indicate significance at the 1%,5%,and 10% level.

Robinhood Popularity	News	Good	Bad	Scheduled	Unscheduled	Earnings	Insider Trading
RH_t^{AHT}	0.299^{***} (8.407)	0.298^{***} (7.805)	0.306^{***} (8.389)	0.335^{***} (5.605)	0.341^{***} (5.719)	0.363^{***} (5.752)	0.467^{***} (5.749)
$News_{i,t}^{AHT}$	0.126 (0.762)	0.525^{***} (2.724)	0.133 (0.619)	2.868^{***} (3.202)	-0.151 (-1.258)	3.992^{***} (2.895)	-0.810^{**} (-1.982)
$News_{i,t}^{AHT} * RH_t^{AHT}$	2.060^{***} (2.758)	2.393^{***} (3.027)	1.488 (1.427)	8.193^{***} (2.076)	0.353^{*} (1.816)	12.055^{**} (2.036)	0.464^{*} (1.752)
Obs.	66,709	63,644	63,126	61,035	65,370	66,248	66,248
Adj. R^2	0.110	0.185	0.094	0.110	0.202	0.108	0.092

Table VI DiD Analysis: Robinhood AHT Extension

We report the results of the DiD analysis around the Robinhood trading hour extension on March 29 2022 for S&P 1500 stocks from 04:00–06:00 p.m. to 04:00–08:00 p.m. EST. The sample period is between Feb 14, 2022, and May 10, 2022. We normalize the dependent variable, i.e., total buyer-initiated (Panel A) and seller-initiated (Panel B) odd-lot trades from 06:00 p.m. to 08:00 p.m. EST (as well as at each venue, i.e., CBOE EDGX, FINRA (ADF), NASDAQ, and NYSE), by the number of total buyer-initiated (Panel A) and seller-initiated (Panel B) odd-lot trades from 04:00 p.m. to 06:00 p.m. EST. $RH_{t,ext}^{AHT}$ is a dummy variable equal to one for days between March 29, 2022, and May 10, 2022, and zero for days between February 14, 2022, and March 28, 2022. The variable $News_{i,t}^{AHT}$ is a dummy variable, equal to 1 if a news event is announced during after-hours trading (AHT), and 0 if no news is announced or if neutral sentiment news is reported during regular trading hours (RTH). Time (Weekday) and Firm Fixed effects are used. T-statistics (in parentheses) are based on standard errors clustered at the firm level. ***,**, and * indicate significance at the 1%,5%,and 10% level, respectively.

Odd-lot Trades	Total	CBOE	FINRA	NASDAQ	NYSE
Panel A: Buyer-initiated					
$RH_{t,ext}^{AHT}$	0.016	0.017***	0.024	-0.013***	0.031***
	(1.148)	(5.897)	(1.434)	(-4.581)	(4.506)
$News_{i,t}^{AHT}$	-0.013	-0.030***	-0.023	0.006	-0.014
	(-0.700)	(-5.962)	(-0.739)	(0.719)	(-0.925)
$RH_{t,ext}^{AHT} * News_{i,t}^{AHT}$	0.034	0.059***	0.122	-0.008	0.069***
	(1.137)	(4.968)	(1.205)	(-0.745)	(2.672)
Obs.	75,585	75,585	75,585	75,585	75,585
Adj. R^2	0.014	0.159	0.017	0.078	0.125
Panel B: Seller-initiated					
$RH_{t,ext}^{AHT}$	0.004	0.009***	0.015	-0.011***	0.013***
	(0.226)	(4.116)	(0.609)	(-4.359)	(2.656)
$News_{i,t}^{AHT}$	-0.027	-0.008	-0.045	0.017**	-0.016
	(-1.083)	(-1.458)	(-0.949)	(2.566)	(-1.549)
$RH_{t,ext}^{AHT} * News_{i,t}^{AHT}$	0.069	0.026***	0.047	-0.026***	0.023
	(1.097)	(3.301)	(0.630)	(-3.217)	(1.499)
Obs.	75,585	75,585	75,585	75,585	75,585
Adj. R^2	0.123	0.014	0.138	0.087	0.138

Table VII DiD Analysis: CBOE Introduction of Retail Priority

We report the results of the DiD analysis around the introduction of the CBOE Retail Priority rule on November 01, 2019, for S&P 1500 stocks. The dependent variables are the realized spreads around buyer-initiated odd-lot trades on different venues (i.e., CBOE EDGX, FINRA (ADF), NASDAQ, and NYSE). The independent variables are defined as follows: $RP_{t,int}^{EDGX}$ equals one if the sample period is after November 01, 2019, and zero otherwise. The variable $Earnings_{i,t}^{AHT}$ is a dummy indicating whether an earnings news event was announced during after-hours trading. To examine the impact of volatility on our results, we classify stocks into terciles based on their absolute return during after-hours trading (AHT) for each trading day. The top tercile represents the stocks with the highest absolute returns, labelled high volatility stocks, while the remaining two terciles constitute the other stocks. We then repeat the difference-in-differences (DiD) regression analysis separately for these two subsamples, reporting the results in Panel B and Panel C. Time (Weekday) and Firm Fixed effects are included. T-statistics (in parentheses) are based on standard errors clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Realized Spread	CBOE	FINRA	NASDAQ	NYSE
Panel A: Earning News				
$RP_{t,int}^{EDGX}$	-0.002***	0.000	-0.001**	-0.001**
	(-3.089)	(1.117)	(-2.283)	(-2.231)
$Earnings_{i,t}^{AHT}$	-0.005*	0.012***	0.000	-0.001
	(-1.876)	(4.319)	(0.131)	(-0.355)
$RP_{t,int}^{EDGX} * Earnings_{i,t}^{AHT}$	-0.008**	-0.002	-0.001	-0.004
	(-2.271)	(-0.456)	(-0.311)	(-1.149)
Obs.	8,455	45,506	7,276	6,124
Adj. R^2	0.362	0.136	0.270	0.386
Panel B: High Volatility Stocks				
$RP_{t,int}^{EDGX}$	-0.001	0.000	-0.001***	-0.001***
	(-1.548)	(0.530)	(-2.656)	(-2.989)
$Earnings_{i,t}^{AHT}$	-0.004	0.012***	-0.007***	-0.003
	(-1.459)	(4.332)	(-2.887)	(-1.135)
$RP_{t,int}^{EDGX} * Earnings_{i,t}^{AHT}$	-0.010**	-0.005	0.001	-0.003
	(-2.455)	(-1.074)	(0.238)	(-0.853)
Obs.	4,999	13,331	4,380	3,909
Adj. R^2	0.354	0.148	0.283	0.339
Panel C: Other Stocks				
$RP_{t,int}^{EDGX}$	-0.003***	0.001	-0.001	0.001
	(-2.802)	(1.195)	(-0.463)	(0.717)
$Earnings_{i,t}^{AHT}$	0.000	0.014**	0.019	0.015**
	(0.032)	(2.484)	(1.568)	(2.146)
$RP_{t,int}^{EDGX} * Earnings_{i,t}^{AHT}$	-0.002	0.001	0.014	-0.018*
	(-0.182)	(0.096)	(0.795)	(-1.779)
Obs.	3,209	32,067	2,538	1,915
Adj. R^2	0.321	0.137	0.221	0.334

Internet Appendix for:

A Pond for Small Fish?
News and (Retail) Trading After-Hours

(Not intended for publication)

Appendix A. Data description

Appendix A.1. After hours data

This appendix describes how we exclude closing auction trades from AHT trades and filter out the errors in data. Closing auction trades are often printed on the tape after the market close, so we need to exclude closing auction trades from the AHT volumes. Over the period 05 Jan, 2004 to 05 Feb, 2009, NYSE paired MOC trades are reported with a specific indicator (TR_STOPIND=Y). Over the period 06 Feb, 2009 to 11 Jun, 2009, there is no specific indicator to report NYSE closing auction, hence, we exclude the largest trades after 4:00 p.m. for the Consolidated Tape Association (CTA), which covers all NYSE-listed and American Stock Exchange- and regional-listed securities. After 12 Jun, 2009, NYSE acution trades are indicated by TR_SCOND=6. Similarly, over the period 01 Jan, 2004 and 21 Sep, 2007, NASDAQ closing cross trades are reported with a specific condition number (TR_SCOND= M). Entries are sometimes duplicated with the condition @6 B. After 24 Sep, 2007, NASDAQ closing cross trades are reported with a specific condition number (TR_SCOND= @6 X). Entries are sometimes duplicated with the condition M or M. Hence, for NYSE auction trades, we exclude either TR_STOPIND=Y or the largest trade after 4:00 p.m. or TR_SCOND contains "6" for different relevant time periods to obtain trading volumes for AHT. For NASDAQ auction trades, we exclude TR_SCOND contains "6" or "M" to obtain trading volumes for AHT. Following Holden and Jacobsen (2014), we filter the transaction and quotation data for errors. First, we exclude trades for which TR_COND is not equal to 00 and trades with a negative price. Second, we remove non-normal quote conditions (A, B, H, O, R, and W). Third, for each exchange or market maker, we delete cases in which the bid of one exchange or market maker is greater than or equal to the ask of the same exchange or market maker. Fourth, we exclude the quote if the quoted spread is greater than \$5.00 or 30% of the midpoint quote, and the bid (ask) price is less (greater) than the previous midpoint -\$2.50 (previous midpoint +\$2.50). In addition, we delete bid

(ask) quotes that have a bid (ask) price or bid (ask) size that is set to be zero or a missing value.

Appendix A.2. Spread Measures

We focus on intraday trading activity measures such as the number of transactions and dollar trading volume as well as liquidity measures such as quoted, effective and realized spreads, and price impact. We are interested in comparing the market quality measures between RTH and AHT.

The first category of liquidity measure is the quoted and effective spread at the firm level. For a given time interval s, the quoted spread is defined as

$$\textit{Percent Quoted Spread}_s = \frac{A_s - B_s}{M_s} \tag{A1}$$

where A_s is the National Best Ask and B_s is the National Best Bid assigned to time interval s and M_s is the midpoint. Aggregating over the sample period, a stock's *Percent Quoted Spread* is the time-weighted average of *Percent Quoted Spread*$_s$ computed over all time intervals. For a given stock, the percent effective spread is on the k^{th} trade is defined as

$$\textit{Percent Effective Spread}_k = \frac{2D_k(P_k - M_k)}{M_k} \tag{A2}$$

where D_k is an dummy variable that equals +1 if the k^{th} is a buy and -1 if the k^{th} trade is a sell and M_k is the midpoint of the quotes assigned to the k^{th} trade by Lee and Ready (1991) convention following Holden and Jacobsen (2014). Aggregating over the sample period, a stock's *Percent effective spread* is a dollar-volume-weighted average of the *Effective Spread*$_k$ computed over all trades.

The second category of liquidity measures the realized spread and price impact. For a

given stock, the percent realized spread is on the k^{th} trade is defined as

$$Percent\ Realized\ Spread_k = \frac{2D_k(P_k - M_{k+5})}{M_k} \tag{A3}$$

where M_{k+5} is the midpoint five minutes after the midpoint M_k. Aggregating over the sample period, a stock's *Percent Realized Spread* is a dollar-volume-weighted average of the *Percent Realized Spread*$_k$ computed over all trades. For a given stock, the percent price impact is on the k^{th} trade is defined as

$$Percent\ Price\ Impact_k = \frac{2D_k(M_{k+5} - M_k)}{M_k} \tag{A4}$$

Aggregating over the sample period, a stock's *Percent Price Impact* is a dollar-volume-weighted average of the *Percent Price Impact*$_k$ computed over all trades. In our calculations, we use logarithmic differences to calculate the ratios.

Appendix A.3. Variables for Random Forest Algorithm

In our RF algorithm, we consider 42 explanatory variables, i.e., features, described in the Table below. Four variables are from CRSP daily files, 20 variables are collected from WRDS Intraday Indicators and we construct the remaining 18 features using TAQ database. Overall, 23 variables are related to RHT, and 19 variables are associated with AHT. In Panel A of Figure 3, we include 37 variables, both RTH and AHT. In Panel B of Figure 3, we use 41 variables, excluding the number of buyer-initiated odd-lots and including five venue-specific variables: CBOE, FINRA (ADF), NASDAQ, NYSE and NYSE ARCA, and OTHERS (smaller exchanges) buyer-initiated odd-lot trades.

Table A.1 Description of Variables

The table provides the list of variables that are used in Random Forest Machine Learning Algorithm

Regular Trading Hour (RTH) Variables			
#	Definition	Data source	Description
1	Daily absolute return	CRSP	abs(ret)
2	Daily return	CRSP	ret
3	Daily price	CRSP	prc
4	Daily share volume	CSRP	vol
5	Absolute percent order imbalance (number of retail trades)	WRDSii	bs_ratio_retail_num
6	Absolute value of buy trade volume minus sell trade volume using Lee & Ready	WRDSii	abs (BuyVol_LR - SellVol_LR)
7	Absolute value of total number of buys minus sells using Lee & Ready	WRDSii	abs (BuyNumTrades_LR - SellNumTrades_LR)
8	Buy trade volume minus sell trade volume signed using Lee & Ready	WRDSii	BuyVol_LR - SellVol_LR
9	Effective spread (dollar-weighted, in percent) using Lee & Ready	WRDSii	effective_spread
10	High-low price ratio	WRDSii	(2*(price_high_m-price_low_m)/(price_high_m+price_low_m))
11	Intraday volatility, second-by-second, trade-based	WRDSii	ivol_t
12	Intraday volatility, second-by-second, quote-based	WRDSii	ivol_q
13	Number of odd-lot trades	WRDSii	oddlotnumber_trade
14	Number of trades using Lee & Ready	WRDSii	total_trade
15	Price impact (dollar-weighted, in percent) using Lee & Ready	WRDSii	price_impact
16	Quoted spread (time-weighted, in percent)	WRDSii	quoted_spread
17	Realized spread (dollar-weighted, in percent)	WRDSii	realized_spread
18	Total number of retail trades	WRDSii	total_trade_retail
19	Total number of retail buys minus sell	WRDSii	BuyNumTrades_Retail - SellNumTrades_Retail
20	Total number of buys minus total number of sells signed using Lee & Ready	WRDSii	BuyNumTrades_LR - SellNumTrades_LR
21	Value-weighted average trade price of buys minus sells using Lee & Ready	WRDSii	vwavg_buy_price_LR - vwavg_sell_price_LR
22	Variance ratio 1 (15-second/3*5-second)	WRDSii	var_ratio1
23	Variance ratio 2 (1-min/4*15-second)	WRDSii	var_ratio2
After Hour Trading (AHT) Variables			
1	Absolute Value of After Hour Return	TAQ	abs(return_aht)
2	After hour trading return	TAQ	return_aht
3	Effective spread (dollar-weighted, in percent) using Lee & Ready	TAQ	effective_spread_aht
4	Number of trades	TAQ	n_trades
5	Number of quotes	TAQ	n_quotes
6	Number of odd-lot trades	TAQ	total_oddlot
7	Number of buyer initiated odd-lot trades	TAQ	buy_oddlot
8	Number of seller initiated odd-lot trades	TAQ	sell_oddlot
9	Overnight return	TAQ	ret_overnight
10	Price impact (dollar-weighted, in percent) using Lee & Ready	TAQ	price_impact_aht
11	Quoted spread (time-weighted, in percent)	TAQ	quoted_spread_aht
12	Realized spread (dollar-weighted, in percent)	TAQ	realized_spread_aht
13	Share volume ($)	TAQ	dollar_volume_aht
14	High-low price ratio	WRDSii	(2*(price_high_a-price_low_a)/(price_high_a+price_low_a))
After Hour Trading (AHT) Variables by Venue			
1	CBOE buyer initiated odd-lot trades	TAQ	cboe_buy_oddlot
2	FINRA buyer Initiated odd-lot trades	TAQ	finra_buy_oddlot
3	NASDAQ buyer initiated odd-lot	TAQ	nasdaq_buy_oddlot
4	NYSE & NYSE ARCA buyer initiated odd-lot	TAQ	nyse_buy_oddlot
5	Others buyer initiated odd-lot	TAQ	others_buy_oddlot

Appendix B. Robustness: Random Forest Algorithm

Appendix B.1. Surrogate Tree

The surrogate tree approach is one of the most widely used machine learning techniques to explain the predictions of a complex machine learning algorithm such as Random Forests or Neural Networks (Craven and Shavlik, 1995). The Decision Tree-based surrogate tree model is useful to approximate the complicated model's predictions due to its interpretability. The approach involves three stages: (i) train the complex model, (ii) capture the predictions from the complex method, (iii) train the decision tree-based surrogate model to approximate the predictions of the complex model.

We use a straightforward three-level tree, which is a piecewise constant function with only eight values (leaves) to approximate the Robinhood Popularity. Figure B.1 illustrates the results. It shows that CBOE EDGX buyer-initiated odd-lot trade is the most important variable and it enters the tree three times at the top two levels of the decision tree. Robinhood Popularity is associated with extreme after-hours price movements (High-Low Ratio (AHT)) and a low level of liquidity, specifically low total odd-lot trading.

Appendix B.2. Shap Value

SHAP (Shapley Additive exPlanations, (Lundberg and Lee, 2017)) is another popular model to rank the variables (i.e., features) in machine learning algorithms. The model uses the cooperative game theory to derive the Shapley values. SHAP model assigns a weighted average gain or impact to each feature that is used in the machine learning algorithm, quantifying its contribution to a specific prediction. This is achieved by analyzing all possible subsets of variables and calculating how adding a variable f changes the model's output for the given observation x. Figure B.2 shows the results. It confirms that CBOE EDGX buyer-initiated odd-lot trade has the highest power to explain Robinhood Popularity.

Appendix B.3. XGBoost Feature Importance

Extreme Gradient Boosting, or XGBoost, is a distributed gradient-boosted decision tree (GBDT) machine learning toolkit. It is one of the top machine learning algorithms for tasks including regression and offers parallel tree boosting. It is often used due to its high predictive accuracy and handling of missing data points. Figure B.3 shows the feature importance of XGBoost algorithm. It confirms the previous results that CBOE EDGX buyer-initiated odd-lot trade has the highest power to explain Robinhood Popularity.

Appendix B.4. Feature Importance - Cross Validation

Overfitting is one of the main issues in implementing machine learning algorithms. To avoid this problem, one of the cross-validation techniques must be conducted. In machine learning, cross-validation is a method for assessing a model's performance on unknown data. It entails splitting the given data into many folds or subsets, training the model on the remaining folds, and utilizing one of these folds as a validation set. This procedure is carried out several times using a different fold as the validation set each time. A more reliable assessment of the model's performance is generated by averaging the outcomes of each validation phase.

We adopt one of the most common cross-validation techniques, k-fold cross-validation analysis. In K-Fold Cross Validation, the dataset is divided into k folds or subsets, and all of the subsets are trained, with one (k-1) subset set aside for the trained model's evaluation. This approach iterates k times, each time using a distinct subset put aside for testing. Figure B.4 shows the 5-fold average cross-validation feature importance. Similarly, the results indicate that CBOE EDGX buyer-initiated odd-lot trade has the highest explanatory power.

Figure B.1. Surrogate Tree

This figure plots the Surrogate Decision Tree model. It constructed with three-level tree and a piecewise constant function with eight leaves. We include 41 observations as in Panel B of Figure 4.

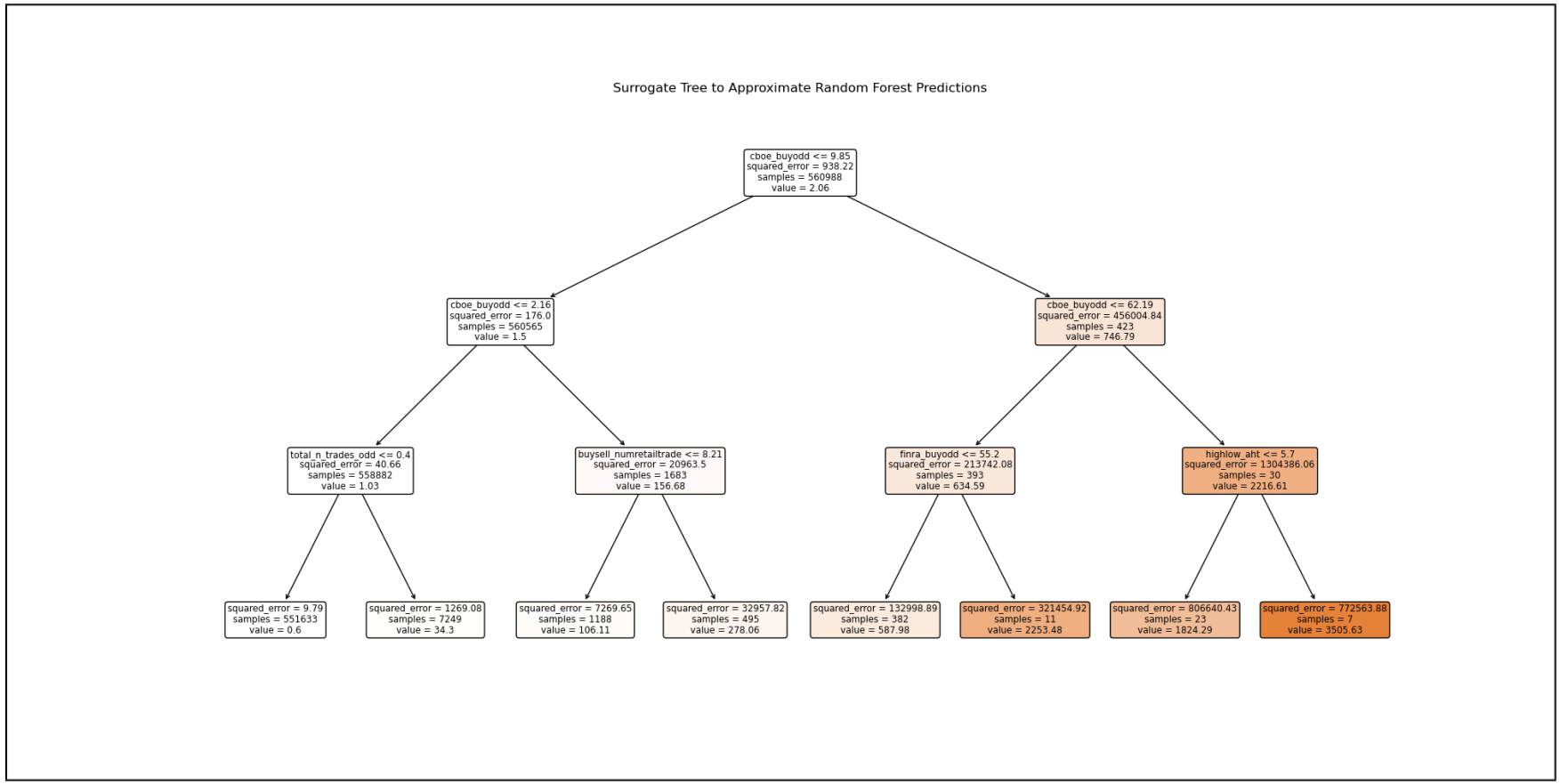


Figure B.2. Shap Value

This figure plots the rank of features based on SHAP values (Shapley Additive exPlanations, (Lundberg and Lee, 2017)). We include 41 observations as in Panel B of Figure 4..

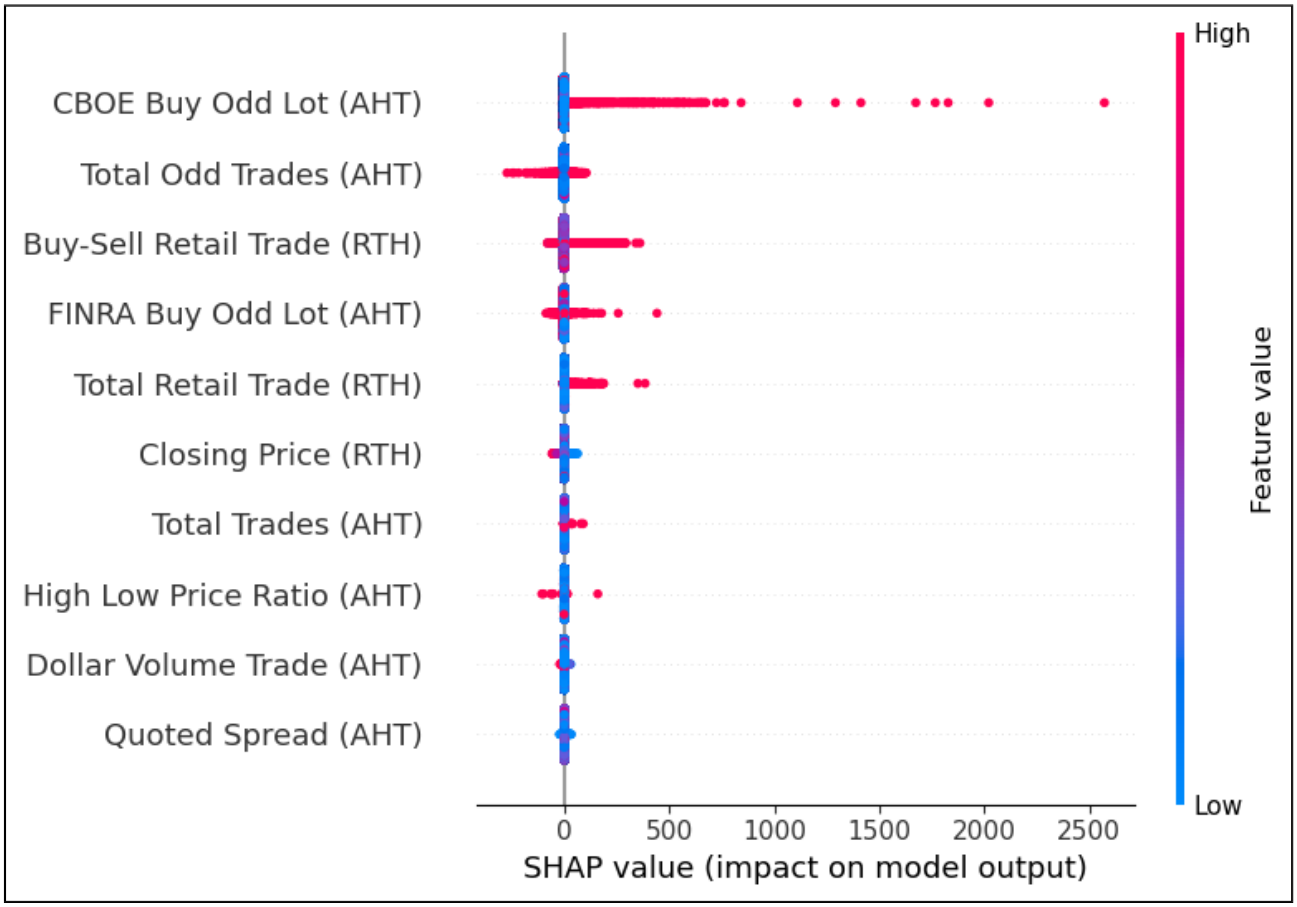


Figure B.3. XGBoost Feature Importance

This figure plots the feature importance of Extreme Gradient Boosting, or XGBoost machine learning algorithm. We include 41 observations as in Panel B of Figure 4.

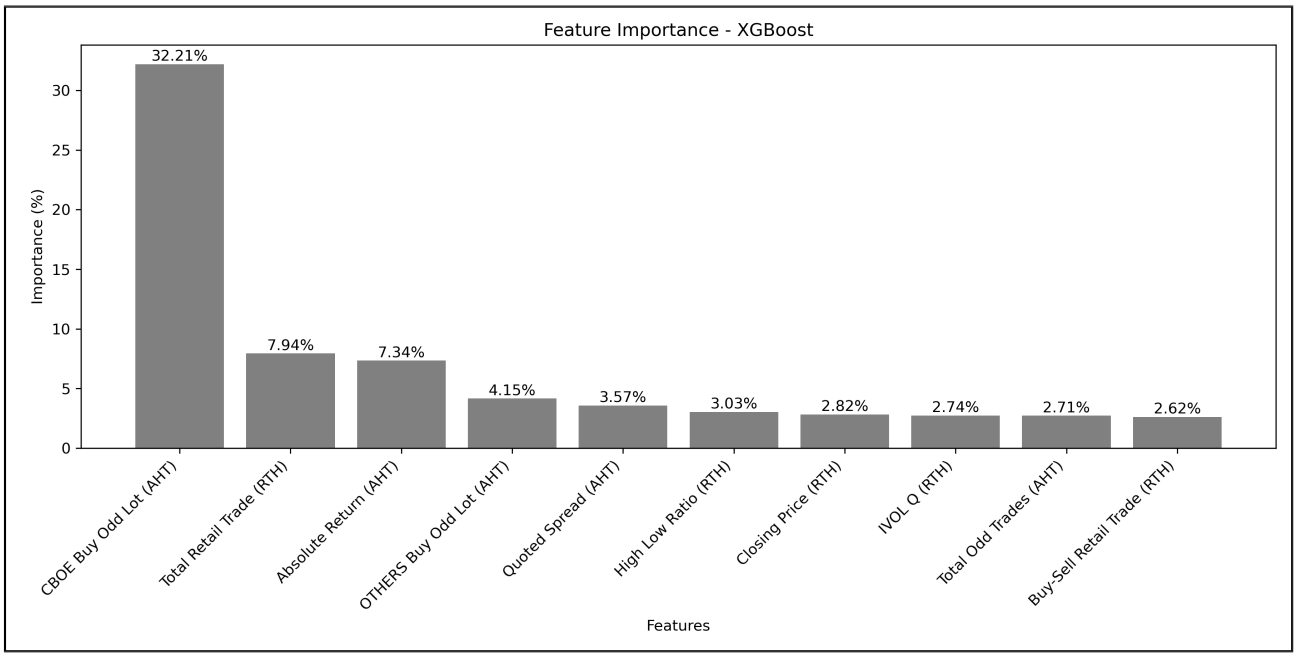


Figure B.4. Feature Importance - Cross-Validation

This figure plots the 5-fold average cross-validation feature importance using the Random Forest algorithm. The sample period is from May 3, 2018, to May 27, 2020. We include 41 observations as in Panel B of Figure 4.

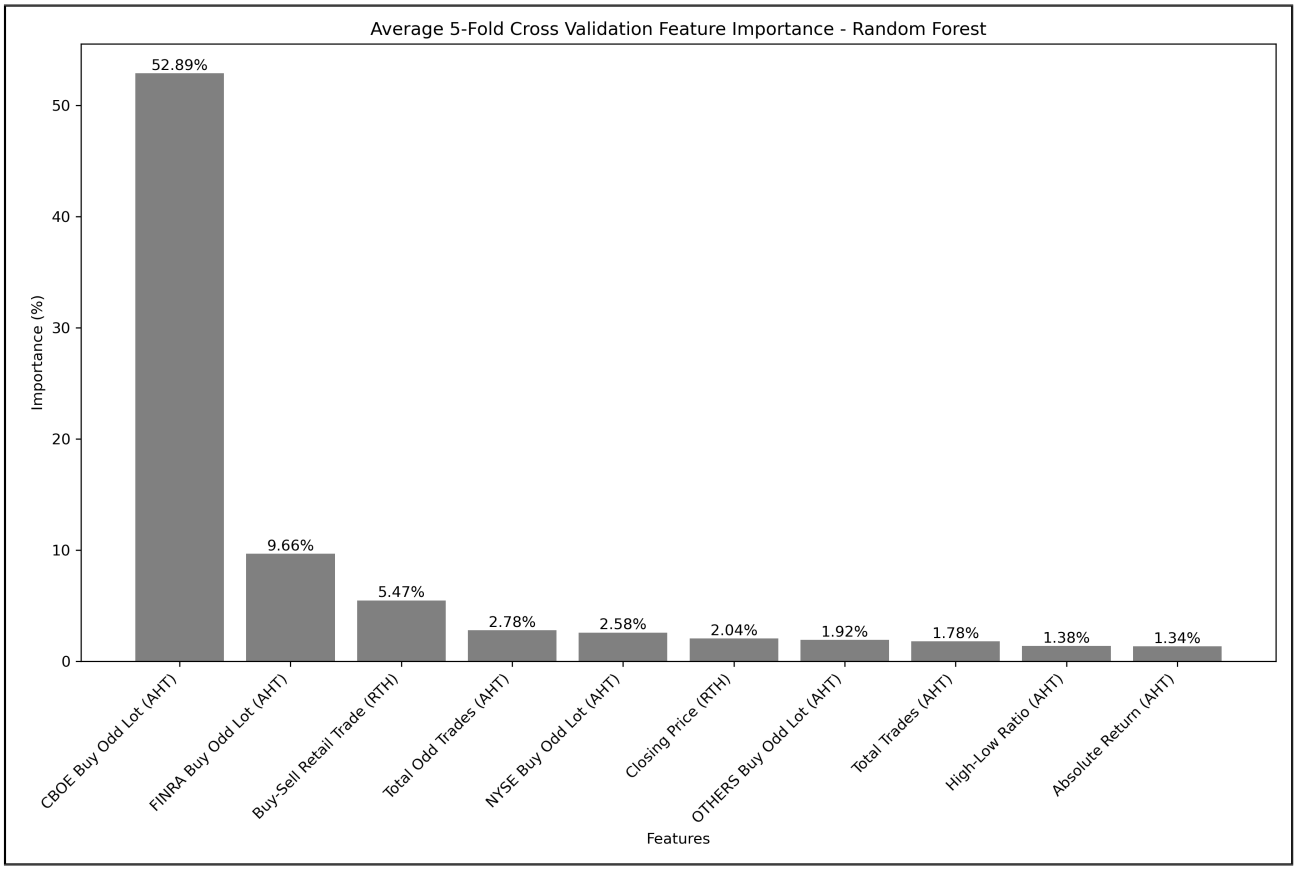
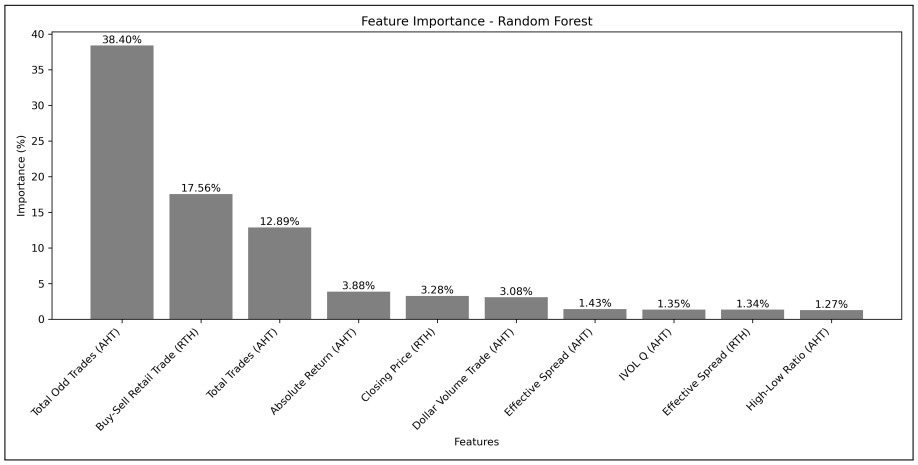


Figure B.5. Feature Importance - Odd-lot Trades (Without Trade Sign)

This figure ranks features by their importance according to Random Forest's internal procedure that ranks features based on the total reduction in Gini impurity (a default option that aggregates the importance of each feature across all splits where the feature was used). The target variable is the absolute value of the difference in the number of users holding S&P 1500 constituents on Robinhood for each day between 04:00 p.m. and 08:00 p.m. AHT odd-lot trades are not signed as buyer or seller-initiated trades. In Panel B, the trading venues include CBOE EDGX Exchange, platforms that report to FINRA alternative display facility (ADF), NASDAQ, NYSE (ARCA), and other smaller trading platforms. The sample period is from May 3, 2018, to May 27, 2020. Explanatory variables (features) are defined in Internet Appendix Table A.1.

(a) Feature Importance



(b) Feature Importance - By Venue

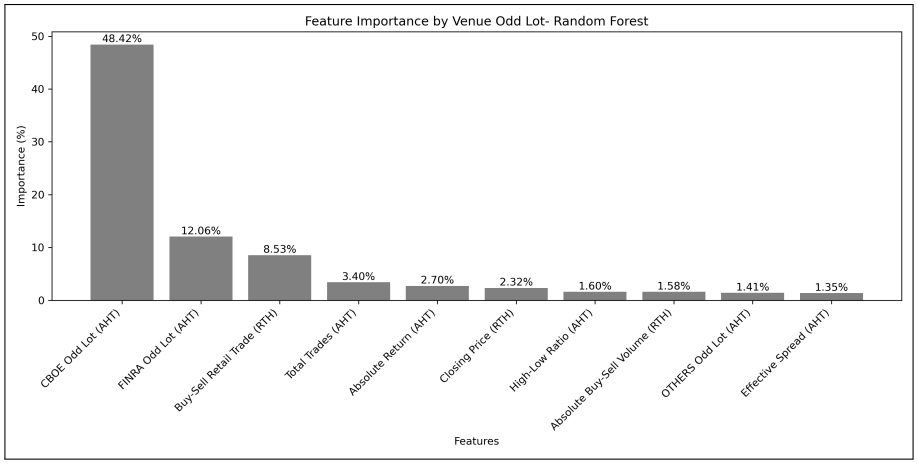


Figure B.6. Feature Importance - S&P 500 Stocks

This figure ranks features by their importance according to Random Forest's internal procedure that ranks features based on the total reduction in Gini impurity (a default option that aggregates the importance of each feature across all splits where the feature was used). The target variable is the absolute value of the difference in the number of users holding S&P 500 constituents on Robinhood for each day between 04:00 p.m. and 08:00 p.m. In Panel B, the trading venues include CBOE EDGX Exchange, platforms that report to FINRA alternative display facility (ADF), NASDAQ, NYSE (ARCA), and other smaller trading platforms. The sample period is from May 3, 2018, to May 27, 2020. Explanatory variables (features) are defined in Internet Appendix Table A.1.

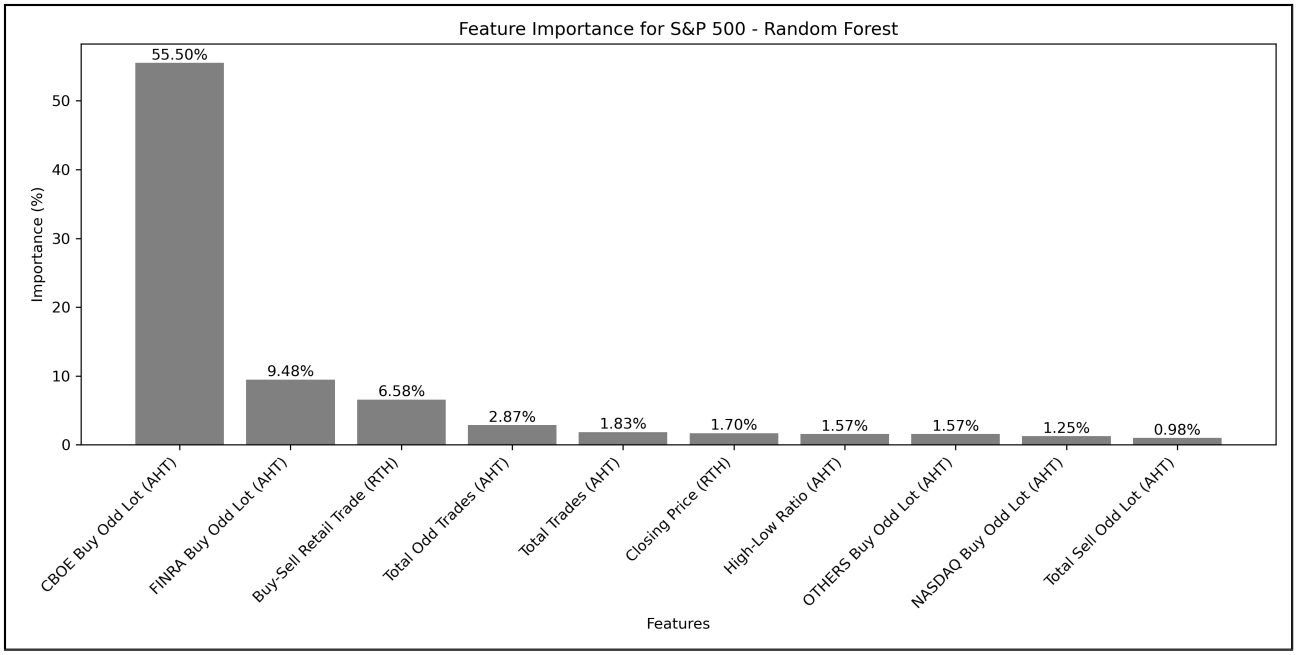
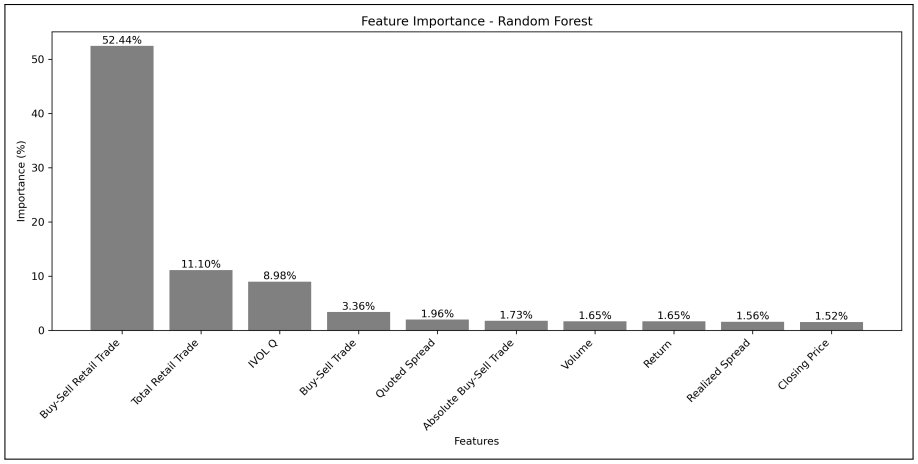


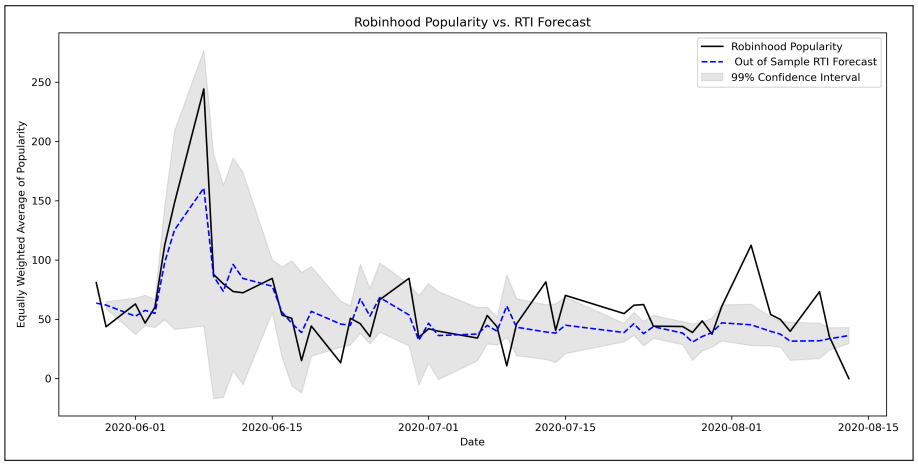
Figure B.7. Feature Importance and Retail Popularit Forecast - RTH

This figure ranks features by their importance according to Random Forest's internal procedure that ranks features based on the total reduction in Gini impurity (a default option that aggregates the importance of each feature across all splits where the feature was used). The target variable is the absolute value of the difference in the number of users holding S&P 1500 constituents on Robinhood for each day between 09:30 a.m. and 04:00 p.m. Panel B shows the out-of-sample predicted and actual values of the absolute value of the difference in the number of users holding SP 1500 constituents on the Robinhood platform for each day between 09:30 a.m. and 04:00 p.m. We use the RF Algorithm and split our initial sample period (from May 3, 2018 to May 27, 2020) as training (80%) and test sample (20%). We use the remaining 10% of the Robintrack data, from May 28, 2020 to August 13, 2020 as the out-of-sample period. The shaded areas show the rolling 99% confidence interval. Explanatory variables (features) are defined in the first panel (23 variables) of Internet Appendix Table A.1.

(a) Feature Importance



(b) Robinhood Popularity Forecast



Appendix C. Two-way Fixed Effects Regressions

This analysis examines the market's reaction to news in terms of the total number of buyer-initiated odd-lot trades as well as trades across individual venues (CBOE EDGX, FINRA (ADF) NASDAQ, NYSE, and other smaller exchanges). We focus on a window of five days before and five days after a news event. The variable News is a dummy variable, taking the value of 1 if a news event is announced during after-hours trading (AHT) and 0 if there is no news or if daily neutral sentiment news is reported during regular trading hours (RTH), as classified by RavenPack. The sample period spans from August 1, 2018, to October 31, 2022. To estimate the impact of news events, we employ a two-way fixed effects regression model with both firm and day-fixed effects, clustering standard errors by firm and date to account for potential within-group correlation. The model includes a constant, which captures the average effect on days outside the event window (i.e., on all other days in the dataset). The regression model is as follows:

$$y_{i,t} = \beta_0 + \beta_1 news_{i,t}^{AHT} + \beta_{2-6} Lag_{i,t-1,t-5}^{news} + \beta_{7-11} Lead_{i,t+1,t+5}^{news} + \epsilon_{i,t} \tag{C1}$$

where $y_{i,t}$ is the number of buyer-initiated odd-lot trades, $Lag_{i,t-1,t-5}^{news}$ and $Lead_{i,t+1,t+5}^{news}$ are the dummy variables indicating the 5-day window around the (scheduled, unscheduled, earnings, insider trading) news event. The figure reports 95% confidence intervals, based on standard errors that are double-clustered by stock and date. For unscheduled news events, we exclude any scheduled news announcements that occur on the same day. The data is winsorized at 0.05% and 99.50%.

Figure C.1. Scheduled News

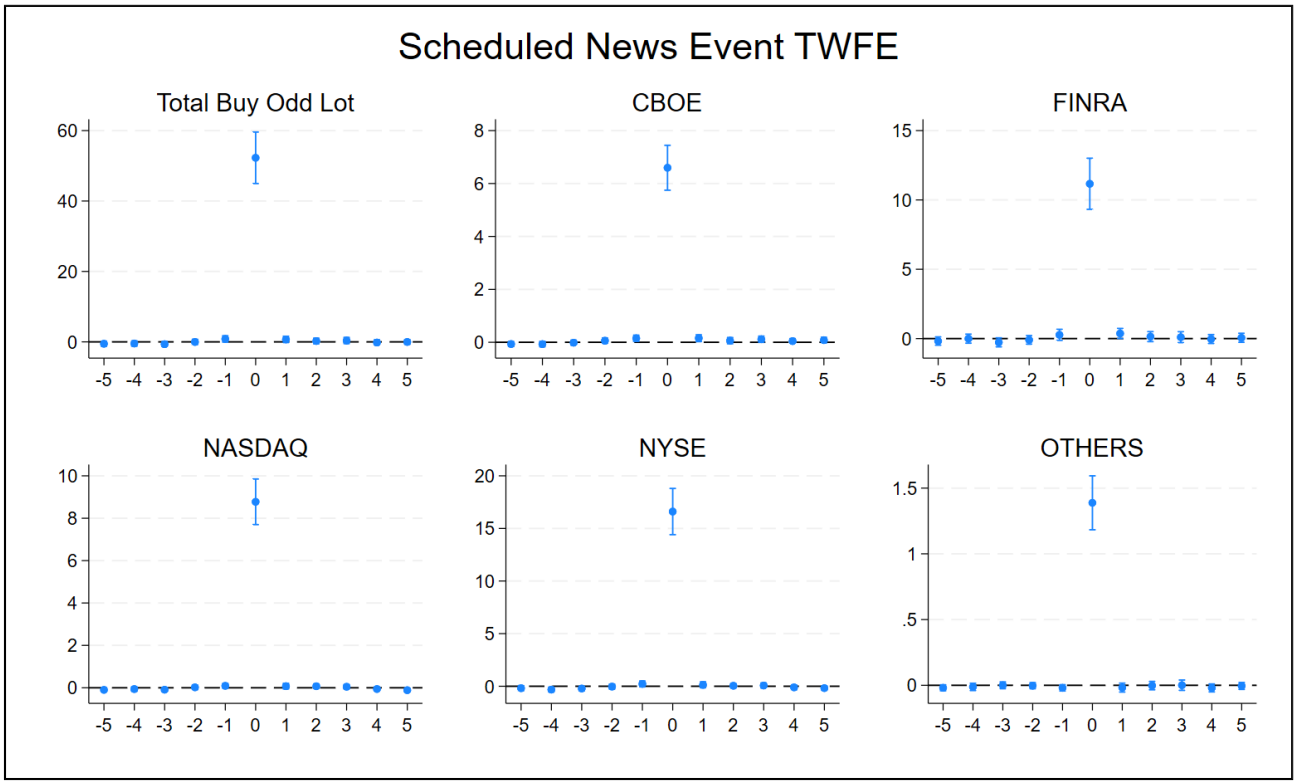


Figure C.2. Unscheduled News

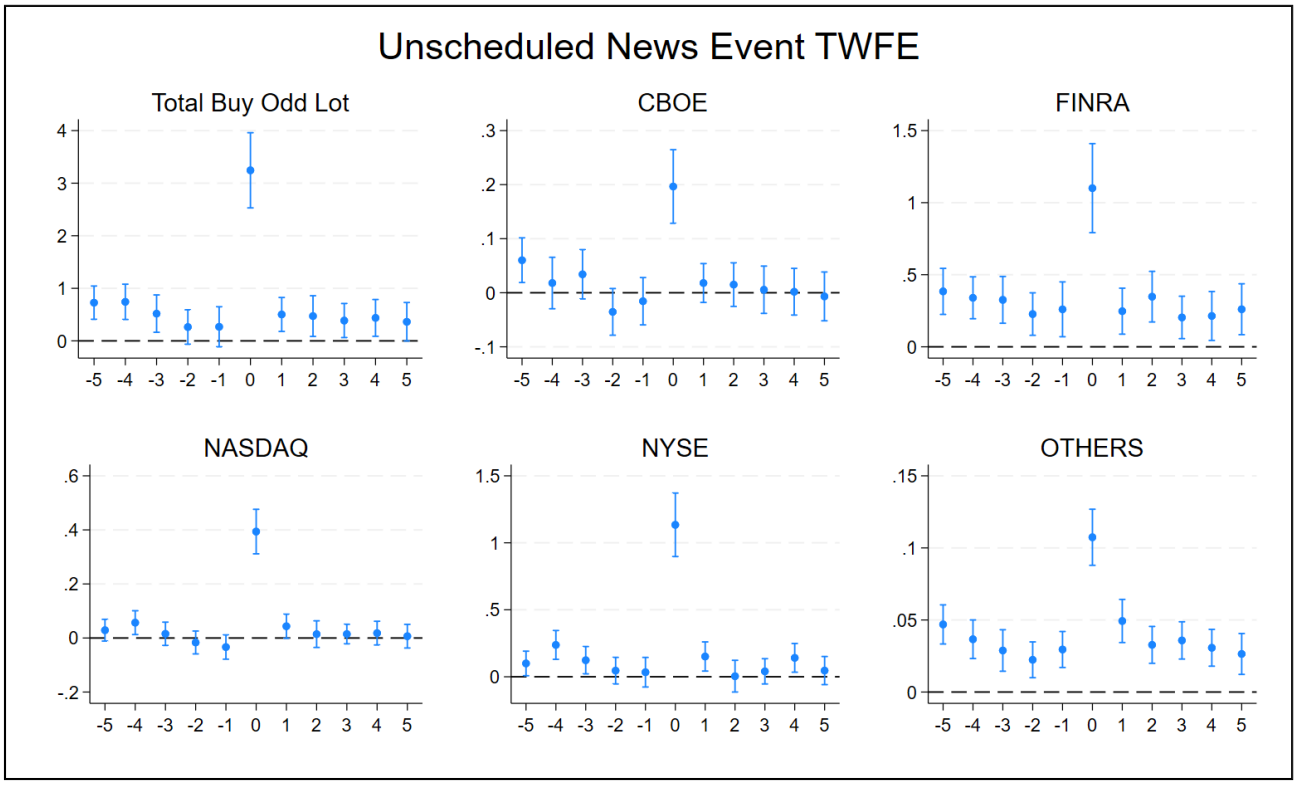


Figure C.3. Earnings News

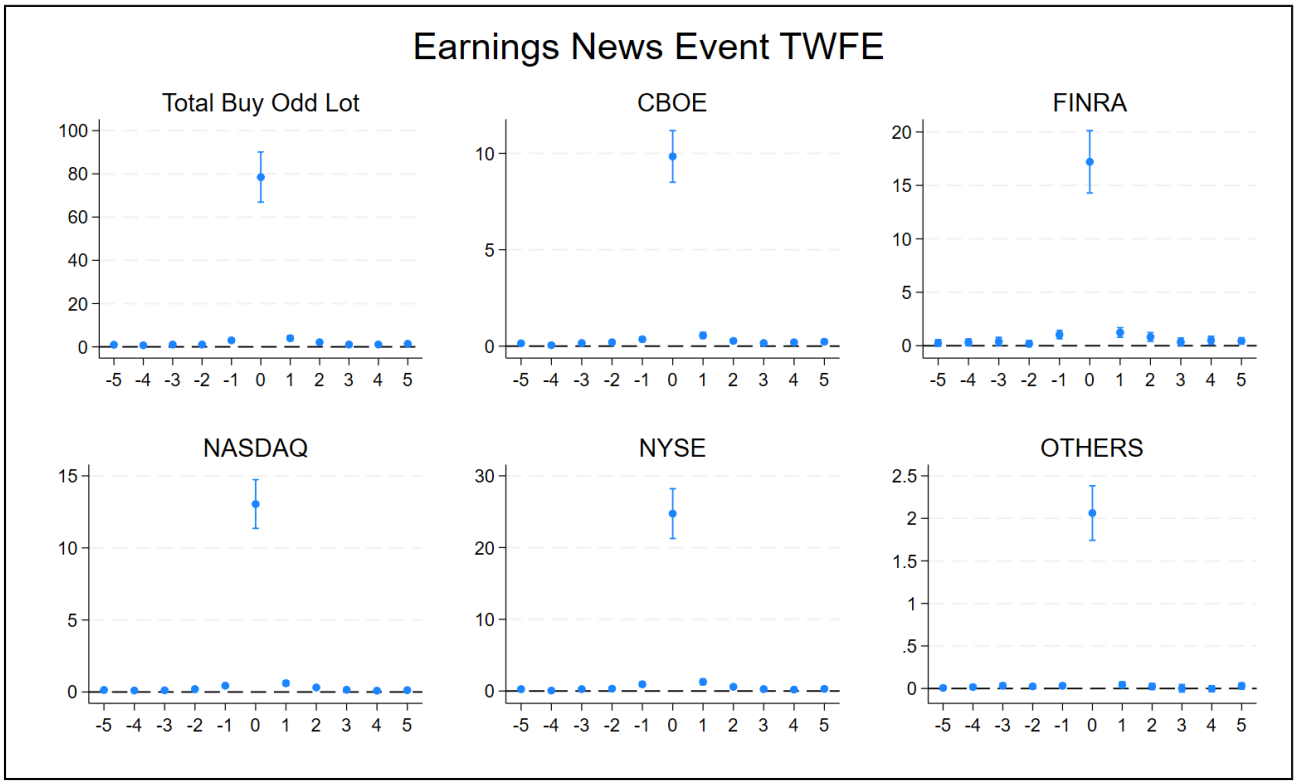
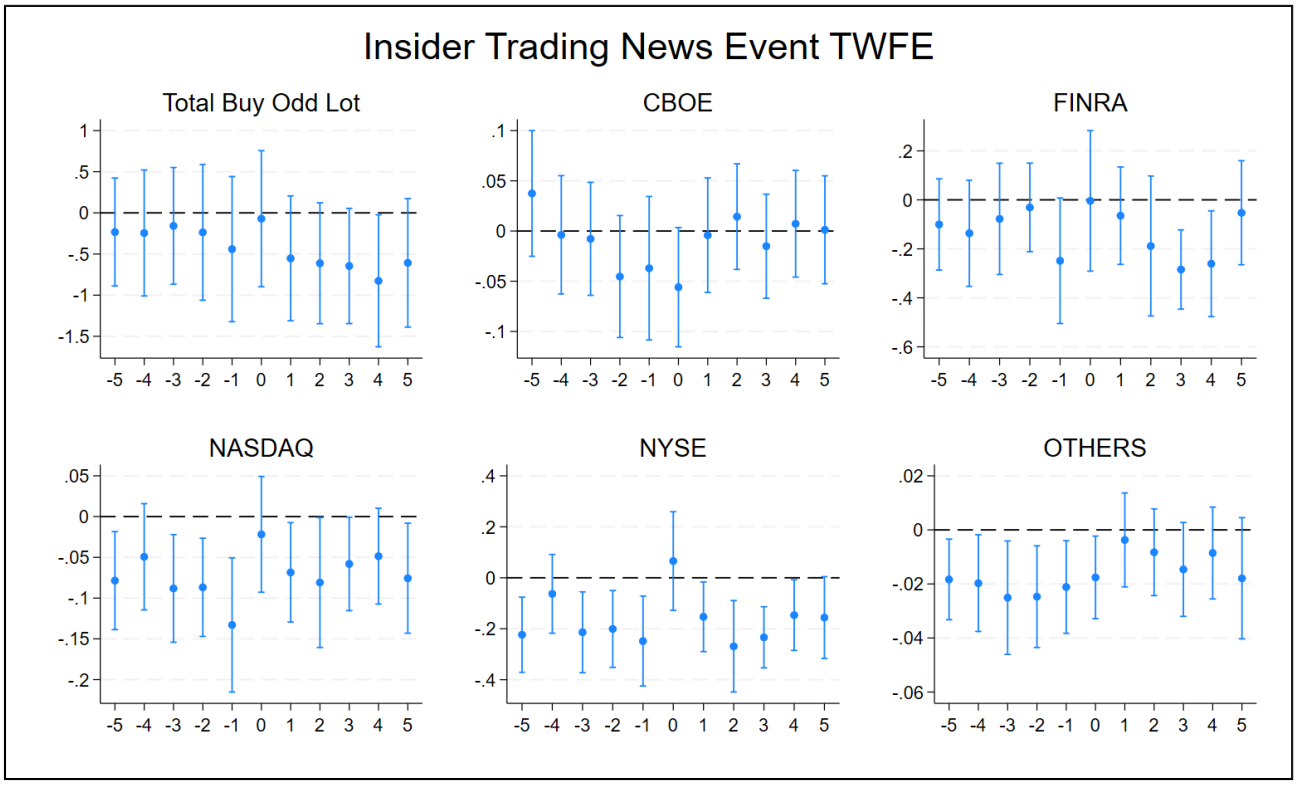


Figure C.4. Insider Trading News



Appendix D. Positive Earnings News

To select the top 10 stocks, we use the Robintrack period (May 2018-August 2020) and sort the stocks based on their retail popularity. We identify the first event by selecting the firm and date with the highest absolute difference in popularity and then compare this event with the RavenPack dataset to match the timing of the news associated with the event. We include only earnings announcement events, as defined by entries where the group is "Earnings" and the type is "Earnings" in the RavenPack dataset, and where the Global Event Novelty Score (G_ENS) equals 100. Events occurring before 04:00:00 pm EST are excluded to avoid the immediate effects of extended trading hours and closing auction during regular trading hours. This exclusion ensures that our event window, defined as 5-minute before to 5-minute after the event, is not contaminated by these effects. After identifying the events and companies (10 companies and 98 events), we extended our sample period to cover August 1, 2018, to October 31, 2022. Several restrictions are applied to include an event in the final analysis: (i) events are excluded if there is any non-neutral RavenPack news sentiment score before the event window, to eliminate potential contamination from other news; (ii) events are dropped if the accumulated adjusted RavenPack news sentiment score after the event is not positive; (iii) events are excluded if the earnings news has a negative RavenPack news sentiment score; and (iv) events are dropped if the event window return (over 10 minutes) is negative. As a result, our final sample consists of 10 companies and 56 events. Table [D.1] presents the final sample of 56 events, along with the event window returns and cumulative adjusted RavenPack news sentiment scores for each event.

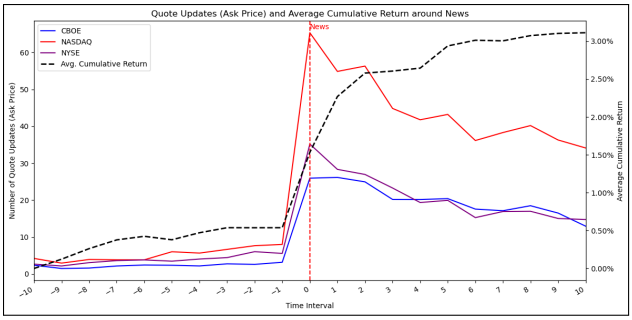
Table D.1
The table provides the list of events with their date and time as well as accumulated adjusted sentiment score and event window returns that we use in the positive earnings news analysis.

Date	Time	Firm	Sentiment Score	Return
2019-01-29	16:30:00	Apple Inc.	0.36	3.04%
2019-07-30	16:30:00	Apple Inc.	0.12	3.07%
2019-10-30	16:30:00	Apple Inc.	0.42	1.93%
2020-01-28	16:30:00	Apple Inc.	1.28	2.36%
2020-04-30	16:30:00	Apple Inc.	2.04	2.20%
2020-07-30	16:30:00	Apple Inc.	1.06	4.14%
2021-04-28	16:30:00	Apple Inc.	1.46	2.88%
2021-07-27	16:30:00	Apple Inc.	1.94	0.60%
2022-01-27	16:30:00	Apple Inc.	1.68	2.02%
2022-04-28	16:30:00	Apple Inc.	1.36	2.43%
2022-10-27	16:30:00	Apple Inc.	0.58	1.25%
2019-01-29	16:15:06	Advanced Micro Devices Inc.	0.78	4.64%
2019-04-30	16:20:04	Advanced Micro Devices Inc.	1.6	8.09%
2019-10-29	16:15:10	Advanced Micro Devices Inc.	1.8	2.42%
2020-07-28	16:15:08	Advanced Micro Devices Inc.	0.62	5.94%
2021-01-26	16:10:01	Advanced Micro Devices Inc.	1.2	1.08%
2021-04-27	16:10:01	Advanced Micro Devices Inc.	1.16	2.68%
2021-07-27	16:15:01	Advanced Micro Devices Inc.	1.52	3.60%
2021-10-26	16:15:02	Advanced Micro Devices Inc.	1.32	1.20%
2022-02-01	16:15:01	Advanced Micro Devices Inc.	1.34	5.77%
2022-05-03	16:10:06	Advanced Micro Devices Inc.	1.88	3.66%
2020-07-30	16:18:00	Alphabet Inc.	2.54	0.43%
2019-03-07	16:15:12	Costco Wholesale Corp.	0.82	1.96%
2019-12-12	16:15:09	Costco Wholesale Corp.	0.78	0.07%
2021-09-23	16:15:01	Costco Wholesale Corp.	1.04	0.79%
2021-12-09	16:15:01	Costco Wholesale Corp.	1.58	0.18%
2022-03-03	16:15:01	Costco Wholesale Corp.	0.9	0.59%
2018-10-30	17:15:04	eBay Inc.	0.88	2.78%
2019-01-29	16:15:04	eBay Inc.	0.96	2.12%
2019-04-23	16:15:07	eBay Inc.	1.56	5.37%
2019-07-17	16:15:05	eBay Inc.	2.02	3.61%
2020-07-28	16:15:06	eBay Inc.	1.58	0.05%
2018-10-24	16:15:49	Ford Motor Co.	1.02	3.64%
2019-04-25	16:17:08	Ford Motor Co.	2.06	4.77%
2019-05-16	16:20:03	NVIDIA Corp.	0.34	4.28%
2019-08-15	16:20:05	NVIDIA Corp.	1.26	5.90%
2019-11-14	16:20:04	NVIDIA Corp.	0.86	0.24%
2020-02-13	16:20:04	NVIDIA Corp.	1.78	5.85%
2021-11-17	16:20:01	NVIDIA Corp.	0.82	2.53%
2018-12-20	16:15:00	NIKE Inc.	1.32	9.27%
2019-09-24	16:15:01	NIKE Inc.	2.58	4.01%
2020-03-24	16:15:00	NIKE Inc.	1.02	4.13%
2020-09-22	16:15:00	NIKE Inc.	1.92	6.86%
2020-12-18	16:15:04	NIKE Inc.	2.1	5.03%
2021-03-18	16:15:00	NIKE Inc.	0.92	0.08%
2021-06-24	16:15:00	NIKE Inc.	3.78	3.99%
2021-12-20	16:15:00	NIKE Inc.	1.06	2.54%
2022-03-21	16:15:00	NIKE Inc.	1.08	4.07%
2022-06-27	16:15:00	NIKE Inc.	1.46	2.15%
2018-10-18	16:21:45	PayPal Holdings Inc.	1.14	2.67%
2019-10-23	16:15:43	PayPal Holdings Inc.	0.74	4.62%
2020-07-29	16:18:04	PayPal Holdings Inc.	1.18	3.74%
2021-02-03	16:19:16	PayPal Holdings Inc.	2.04	0.48%
2021-05-05	16:21:12	PayPal Holdings Inc.	0.76	6.49%
2019-07-16	16:15:08	United Airlines Holdings Inc.	2.32	1.58%
2021-10-19	16:30:07	United Airlines Holdings Inc.	1.12	1.15%

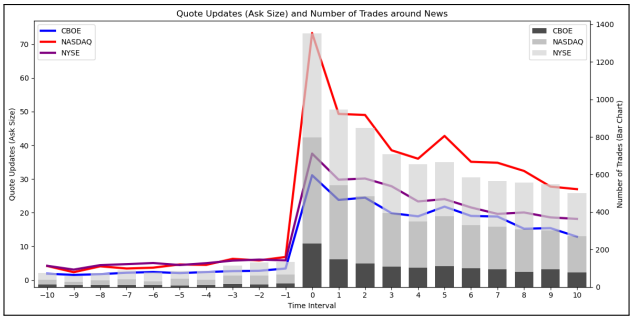
Figure D.1. Positive Earnings News

This figure shows the average number of quote updates on different exchanges around 56 positive earnings news of ten S&P 500 stocks mostly followed by retail investors according to Robinhood popularity. We report the number of quote updates within 30-second intervals that improve the best (ask and bid) price and the number of quote updates that increase the BBO depth both at the best bid and ask levels. We also report the average cumulative return and the number of trades initiated on each exchange within 30-second intervals. The pre-event (post) event window is five minutes sampled at a 30-second frequency. The exchanges include the CBOE EDGX, NASDAQ, and NYSE.

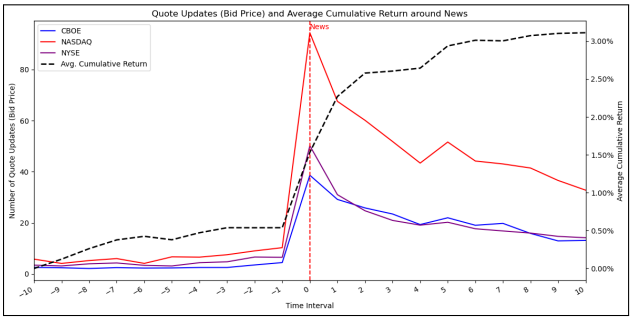
(a) Ask Price



(b) Ask Size



(c) Bid Price



(d) Bid Price

