A Pond with Sitting Ducks?

News and Retail Trading After-Hours

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We examine after-hours trading (AHT) in U.S. equities and document substantial retail participation around scheduled corporate news. We introduce a novel machine learning–based measure of AHT retail activity and use odd-lot trades on Cboe EDGX, an exchange with retail priority, as a proxy for retail participation. AHT retail investors trade without informational or speed advantages, contribute to return reversals, and earn lower liquidity provision profits following the introduction of retail priority. An aggregate news-driven AHT retail portfolio performs poorly. Overall, retail investors face substantial risk in fragmented after-hours markets with no clear evidence of offsetting gains.

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Although most of the trading activity takes place during regular trading hours (RTH), both exchanges and alternative trading platforms offer trading beyond these hours. A substantial share of US corporate news is released in the after-hours market between 4:00 p.m. and 8:00 p.m., highlighting the growing relevance of after-hours trading (AHT) in financial markets (see Figure 1). Prior research emphasizes the price discovery function of the after-hours market, driven by the active participation of institutional investors, informed traders, and high-frequency trading firms (HFTs) (Barclay and Hendershott, 2003; Chakrabarty et al., 2022; Jiang et al., 2012). A key question is whether the recent surge in retail trading (Barber et al., 2022; Bryzgalova et al., 2023; Van der Beck and Jaunin, 2025) extends to AHT.

[Figure 1 about here.]

Our focus is on the evolution of AHT in recent years and studying the role of corporate AHT news in driving AHT activity, particularly of retail investors. We start by analyzing 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 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 trading in the after-hours market.

As shown in Figure 1, we document an increase in AHT dollar volume at the beginning of the sample, around the introduction of Regulation NMS. Following a decline due to the Global Financial Crisis, AHT volume grew steadily, reaching unprecedented levels by the end of our sample. This rise is accompanied by significant market fragmentation (Panel B), in which exchanges such as Cboe EDGX, NASDAQ, and NYSE attract smaller trades. In comparison, larger trades are predominantly executed on off-exchange venues (FINRA).[1] We note that the number of trades more than doubled during the Covid-19 pandemic, with a notable increase in trades on Cboe EDGX. It is important to understand the underlying

[1] 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).

drivers of increased AHT activity in recent years in light of the changes in the US equity trading landscape discussed in Section I.

Our first contribution is providing a comprehensive overview of increasing AHT activity by collecting information on both *scheduled* firm-specific news, such as earnings news (Christensen et al., 2025; Jiang et al., 2012), and *unscheduled* corporate news, such as insider trading news (Baruch et al., 2017; Huang et al., 2020). Using a detailed news dataset collected by RavenPack, we collect news disseminated in the AHT for S&P 1500 stocks during the period January 5, 2004, and October 31, 2022, as well as a more recent sample from 2018. Between May 3, 2018, and August 13, 2020, we also observe retail investor holdings on the Robinhood platform via Robintrack. We confirm that an increase in AHT news circulation coincides with higher AHT trading activity and lower spreads, indicating improved AHT liquidity over time.[2]

Brokerage firms routinely warn retail investors about the inherent dangers of after-hours trading (AHT), citing concerns such as low liquidity, heightened volatility, potential disconnect from other markets, and abrupt price changes linked to news arrival.[3] Despite these warnings, zero-commission retail brokers increasingly facilitate retail access to AHT through gamified platforms (Mantel and Saglam, 2024), and trading in extended hours is a growing business. In May 2023, the Robinhood platform started offering a 24-hour market. NYSE and NASDAQ also started the conversation on round-the-clock trading (Financial Times, 2025). Other Alternative Trading Systems (ATS) already offer nocturnal trading (Eaton et al., 2025). Although these platforms often aim to mitigate price risks for retail investors by restricting retail order submission to limit orders, a crucial question emerges: are these markets, which become increasingly efficient around news days (Christensen et al., 2025), suitable for retail investors? Do these platforms cater to the needs of retail investors by

[2]The average duration between trades dropped from 203 seconds to 51.3 seconds in the post-2018 sample, while the effective spreads declined by 18.6% from 72.5 b.p. to 59 b.p.; however, they are still more than ten times higher than the effective spreads during RTH.

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

implicitly positioning them as liquidity providers[4] to other, presumably larger and faster, market participants? Our study addresses these questions by examining the liquidity provision of retail investors around AHT US corporate news.

We first test whether retail investors participate in AHT despite its risks and the limited choice of order submissions. On August 1, 2018, the Robinhood platform allowed all its regular customers to trade until 6:00 p.m., extending trading on the platform beyond the market close at 4:00 p.m.[5] We use this event 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 AHT retail access via the Robinhood platform. The news-based increased AHT popularity is consistent with the event-driven and attention-induced retail investors hypothesis (e.g., Barber et al., 2022; Da et al., 2011; Fedyk, 2025; Pedersen, 2022) where corporate news attracts retail participation.

Is this evidence specific to the Covid-19 period? Robinhood popularity measure is publicly available until August 13, 2020. Measuring retail trading activity without proprietary datasets remains an important challenge (Barber et al., 2024; Battalio et al., 2024). Several papers capture retail activity with marketable orders from TAQ data (Barber et al., 2022; Boehmer et al., 2021; Jones et al., 2025) or fractional trades (Bartlett et al., 2024; Da et al., 2024). However, most platforms allow AHT only via limit orders for retail investors, and fractional shares are only executed during regular trading hours, so these retail measures cannot be constructed for AHT. Moreover, experimental (Bloomfield et al., 2009; Gozluklu, 2016) and recent empirical evidence (Anand et al., 2025) suggest that retail traders often submit orders less aggressively. Thus, we argue that AHT is an ideal laboratory for capturing retail trading and propose a novel measure of retail trading intensity (RTI) during AHT.

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

[4]In principle, retail traders can trade more aggressively by submitting marketable limit orders, but according to a recent study (Anand et al., 2025), a large fraction (nearly three quarters) of retail limit orders are non-marketable.

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

trading during AHT. The machine learning method reveals that the number of (buyer-initiated) odd-lot trades during AHT from Cboe EDGX is the most important predictor of retail popularity.[6] This exchange offers a platform with retail priority (Cboe, 2024), which seems to be the likely destination for passive Robinhood retail orders for execution.

Can we then use odd-lot trades on Cboe EDGX as a simple proxy for AHT retail participation? To answer this question, we provide further evidence of the reaction of odd-lot trades to different types of news. We observe a particular increase in odd-lot trades on Cboe EDGX around the Covid-19 period, coinciding with the entry of retail investors during the pandemic. Yet, the rise in odd-lot trades on all platforms on news days makes the retail identification based on 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 extension of the after-hours trading to 8:00 p.m. We test whether the odd-lot trades help us identify retail activity driven by firm-specific news. Our results confirm that odd-lot trades from Cboe EDGX provide a strong signal for retail participation in AHT on firm-specific news days.[7]

We next turn to liquidity provision by retail investors during AHT. We study the interaction between AHT liquidity and retail participation by running panel regressions of next-day returns and AHT liquidity measures on our proposed extrapolated retail trading intensity (RTI) measure and their interaction with AHT returns and (earnings) news. The results reveal that our retail proxy is a key driver of short-term return reversals in line with uninformed liquidity provision (Glosten and Milgrom, 1985; Campbell et al., 1993; Nagel, 2012). It also coincides with reduced spreads, providing evidence of increased liquidity thanks to retail activity. However, the conclusion is different on news days, suggesting increased spreads

[6] We repeat the same analysis (reported in Online Appendix Figure C.7) 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.

[7] On January 26, 2021, when Elon Musk's tweet triggered Gamestop (GME) rally during AHT, both RTI and buyer-initiated odd lot trades on all trading platforms jumped, but the magnitude of the jump was most sizeable on Cboe EDGX. More importantly, two days later, when Robinhood restricted the purchases of GME stock (and other meme stocks), buyer-initiated odd-lot trades on Cboe EDGX declined by 95%.

with reduced price impact (Bloomfield et al., 2009), hinting at elevated adverse selection due to speed rather than incorporation of news (Brogaard et al., 2019; Foucault et al., 2016; Hoffmann, 2014).

To the best of our knowledge, we are the first paper studying retail priority on Cboe EDGX. Most lit exchanges follow price-time priority rules, meaning that orders that arrive at the same price are executed based on their chronological order, giving priority to those traders whose orders arrive first to the limit order book. Cboe EDGX introduced a novel retail priority rule on November 1, 2019 (Cboe, 2024), promising superior execution quality for retail investors who would jump the queue of other orders at the same price. Do retail investors benefit from AHT retail priority, or are they still exposed to other opportunistic traders with speed advantage on news arrival days (Hoffmann, 2014)? We answer this question by focusing on the profits from liquidity provision around the introduction of retail priority on Cboe EDGX. Our analysis reveals that profits to liquidity provision measured by realized spreads decrease significantly on days of AHT earnings news, but only on Cboe EDGX. The reduction comes from stocks with high AHT return volatility and high BBO depth. Our findings provide compelling evidence that limit orders, particularly those benefiting from retail priority, expose retail investors to considerable picking-off risk on days of uncertain earnings news.

We also provide microscopic evidence on intraday AHT liquidity provision around two events: i) Apple's (AAPL) earnings news on July 30, 2020, at 4:30 p.m.[8] and ii) Gamestop (GME) frenzy on January 26, 2021, triggered by Elon Musk's tweet "GameStonk" at 4:08 p.m. The tale of two events helps us compare the reaction of market participants on different exchanges to scheduled and unscheduled news. High-frequency data suggest that retail investors have limited ability to enjoy retail priority in liquidity provision, as more sophisticated traders exploit low-latency technology to react to public news (Christensen et al., 2025). Quote activity and price paths are also in line with uninformed liquidity pro-

[8]We also extend the analysis to a larger set of earnings news events and obtain similar results.

vision (Gregoire and Martineau, 2022), suggesting that event-driven market participation in after-hours markets may not be the right choice for unsophisticated retail investors.

Finally, we construct an aggregate news-driven AHT retail portfolio that reflects the attention-based market participation of the Robinhood crowd around AHT firm-specific news. The poor performance of this portfolio relative to alternatives such as the Robinhood representative portfolio (Fedyk, 2025; Van der Beck and Jaunin, 2025; Welch, 2022) and the market portfolio shows no clear evidence of a tangible gain for AHT retail participation. Overall, our analysis reveals significant adverse effects on retail investor outcomes in the fragmented after-hours market and raises important questions about the evolving structure of extended hours trading.

The remainder of the paper is organized as follows: In Section I, we discuss the motivation for AHT. Section II introduces the data sources. Section III describes the AHT trading and the AHT news information environment, IV links firm-specific news to AHT retail trading. Section V provides results on AHT liquidity provision. Section VI discusses the results of the portfolio analysis. Section VII concludes.

I. Motivation for After-Hours Trading

AHT trading is not a new phenomenon (Barclay and Hendershott, 2003), but the current trading environment is different. We first need to understand the appeal of AHT for market participants. In an environment where corporate news is frequently released after the market closes, it is clear why institutions, informed hedge funds, and event-driven HFTs would like to have access to AHT, and in fact, they do (Barclay and Hendershott, 2003; Chakrabarty et al., 2022; Christensen et al., 2025; Jiang et al., 2012). The question we pose in this paper is whether retail investors benefit from this access to AHT, given the risks mentioned in the introduction.

Let us unpack the potential risks with a very simplified illustration. Suppose a retail

investor wants to sell ten shares of an S&P 1500 constituent (e.g., AAPL) at $100 per share.[9] During the RTH, they can either submit a market order and pay the half-spread around 26¢ (see Table I) or submit a limit order to earn the half-spread conditional on execution. Trades occur much more frequently during regular trading hours (RTH), with an average interval of just half a second between transactions, compared to more than 50 seconds between trades during AHT (*low liquidity*). If they decide to trade during AHT, they can submit a limit order and pocket a large half-spread of around $6 (see Table III). At first glance, this seems to be an appealing trading opportunity, especially for a patient liquidity provider; however, it ignores an important fact, that is, after-hours markets can be very volatile on news days (*heightened volatility*). Consider a scenario in which positive after-hours earnings news leads to a 1% price move (*abrupt price changes*).[10] The retail investor might be aware of the news; it might well be the trigger for the sale in the first place, but they cannot necessarily monitor the market constantly and react rapidly to the news - that is, by canceling and updating the quote. (Anand et al., 2025) Before they can react, another faster trader can *pick off* the stale limit order at $100 (Copeland and Galai, 1983) while the stock price has moved to $101, leaving the retail investor as a "sitting duck" and resulting in a $4 loss relative to the fair price.

This is a simple version of the current reality. In the modern architecture of US financial markets, zero-commission trading platforms (e.g., Fidelity, Charles Schwab, Robinhood) play a vital role in attracting retail investors. These platforms act as retail brokers, but instead of earning trading commissions, they receive payment for order flow (PFOF) from other intermediaries called wholesalers, e.g., Citadel, Virtu, and Jane Street (Eaton et al., 2022; Parlour and Rajan, 2003; Schwarz et al., 2025). These new players often internalize trades on their own platforms, guaranteeing best execution by offering price improvement:

[9]During the sample period, the average account size is $ 3,500, and each account holder has around three stocks (Fedyk, 2025).

[10]Under the normal distribution with a volatility of 2.56% (See Table III), there is a 70% chance that there would be a price move of at least 1% or more on earning news days, while there is only a 0.06% chance of a similar price move on a random day.

execution at a narrower spread than what is available on public exchanges.[11] The catch is that this process gives wholesalers access to aggregate retail order flow, a very valuable piece of information (hence PFOF) for opportunistic traders.[12] More importantly, these wholesalers often also act as proprietary traders. Endowed with low-latency technologies, they create potential conflicts of interest, a concern the Securities and Exchange Commission (SEC) raised in their proposal for Regulation Best Execution (SEC, 2022).[13]

SEC Rule 606 requires brokerage firms to publish quarterly reports detailing their order routing practices for non-directed customer orders. For example, in the case of Robinhood, all customer orders are non-directed, meaning that Robinhood makes the routing decision. These reports include information on the PFOF received for market, marketable limit, and non-marketable limit orders from each wholesaler. Currently, the PFOF is a higher fixed percentage of the spread during RTH, that is, 12.35% during RTH and 9% during AHT (Robinhood, 2025). However, these disclosures are opaque regarding the revenues from orders submitted during AHT.

It is not obvious why zero-commission retail brokers such as Robinhood, which rely on PFOF for revenues, would offer access to AHT via limit orders. Robinhood routes marketable limit orders to wholesalers and receives a smaller percentage, albeit on a larger spread, during AHT. This is likely to be a small fraction of their revenues as retailers often submit limit orders more passively (Anand et al., 2025; Bloomfield et al., 2009; Gozluklu, 2016). The non-marketable limit orders could also be sent to a wholesaler or be directed to exchanges without generating PFOF. Yet, Robinhood could still receive some rebates from the exchange. From the disclosures, which suggest routing to wholesalers rather than exchanges, it is not obvious whether the routing of AHT orders is an important source of income. Robinhood offered

[11] NYSE and NASDAQ also compete for retail order flow through retail liquidity program (RLP) and retail price improvement program (RPI), respectively. However, these programs are not available during AHT.

[12] The wholesalers also have the agility to offload unbalanced retail order flow onto public exchanges. (Hoffmann and Jank, 2024).

[13] Recent papers also highlight the potential market power of wholesalers (Bryzgalova et al., 2023; Ernst and Spatt, 2024; Huang et al., 2025) in option markets, but there is no option trading after-hours for individual stocks.

AHT only for premium clients until 2018, but gradually allowed all customers to trade during AHT, first until 6:00 p.m., then until 8:00 p.m. in March 2022, and eventually offered 24-hour trading of individual stocks in May 2023 (Eaton et al., 2025). Do these changes serve to attract new customers to the platform? Is it an indirect source of income for trading platforms? What about the wholesalers? These firms constantly monitor retail order flow and have a speed advantage. Along with other event-driven HFTs, they may trade against retail orders using low-latency technology in an environment where the best execution rules (e.g., no trade-throughs) are harder to enforce after-hours in the absence of the National Best Bid and Offer (NBBO). To evaluate this conjecture, we first identify retail trades and then examine whether retail investors benefit from liquidity provision during AHT, particularly around corporate news. We then ask whether financial innovations such as the retail priority offered by Cboe EDGX protect retail investors against picking-off risks during AHT. Finally, we assess the performance of news-driven aggregate AHT retail portfolios.

II. Data

Our data comes from a variety of sources. For regular trading hours, we use the WRDS intraday indicators to obtain the data. For the after-hours market, 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) refer to trading sessions from 9:30 a.m. to 4:00 p.m. After-hours trading (AHT) refers to a trading session from 4:00 p.m. to 8:00 p.m. NYSE "Closing auction" and NASDAQ "Closing cross" are printed in DTAQ with timestamps right after 4:00 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.[14] Our final sample consists of 6,906,378 stock-day observations for S&P 1500 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 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 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).

We identify AHT news days of a firm as days when non-neutral firm-specific news is an-

[14]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.

nounced only during after-hours trading (AHT). On no-news days, either no news or neutral news is announced during AHT and RTH. RTH news is defined as if news is announced only 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 differentiate 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.[15]

We collect stock-level controls from CRSP, such as price and market capitalization. In the recent sample, from May 2018 to August 2020, we have a direct measure of retail popularity from the retail brokerage firm, Robinhood, via the Robintrack website. We measure AHT retail popularity as the absolute value of the change in the number of Robinhood users holding S&P 1500 constituents between 4:00 p.m. and 8:00 p.m. on each day.

III. After-Hours Trading 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 returns, volatility, trading activity, and intraday liquidity measures for the sample period, January 5, 2004 - October 31, 2022.

[15] Online Appendix Figure A.1 describes the decision tree for news classification.

We report both equal-weighted and value-weighted averages across S&P 1500 constituents. Returns during RTH and AHT are comparable, although RTH returns exhibit higher average volatility. In contrast, trading activity differs across the two sessions. On a value-weighted (equal-weighted) basis, average trading activity is substantially lower during AHT, with only 153.43 (24.26) trades and $27.3 ($3.5) in dollar volume, compared to 47.09 (10.85) thousand trades and $596.93 ($90.08) million during RTH. The larger value-weighted average suggests that larger stocks attract more AHT. The wide range of dollar volume observed during AHT is indicative of infrequent but very large trades.

[Table I about here.]

Liquidity measures also draw a similar picture, suggesting that AHT is shallower with lower BBO depth and higher transaction costs measured in quoted, effective, and realized spreads. Lower BBO depth exposes AHT market participants to price jumps. The AHT realized spread is a larger fraction of the AHT effective spread, reflecting the profitability of liquidity provision. The larger AHT price impact, pronounced in the right tail, highlights the price discovery role of AHT on news days (Barclay and Hendershott, 2003).

A. Firm-specific News

We next explore the link between firm-specific news and AHT activity. We provide the list of corporate news, 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) 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 as information dissemination increases 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 not only by retail investors 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 returns, volatility, trading activity, and market liquidity.

In Table III, we present how AHT returns, volatility, the trading activity, depth, 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. News is a dummy variable, equal to 1 if non-neutral firm-specific news is announced only during after-hours trading (AHT), and 0 if no news or neutral news is announced during AHT and 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). 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 1 in the recent post-2018 period is associated with higher return and volatility, reduced BBO depth and spreads, except for the price impact component of the effective spread. While price impact is expected to increase with the elevated volume of news releases in the recent sample, it is surprising that the price impact is also higher on no-news days, presumably reflecting the increased adverse selection risk in AHT. News days deliver higher returns reflecting higher volatility, 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 observe that RTH news is an important driver of AHT activity, with its impact becoming more pronounced in the recent sample. As expected, volatility and trading are more elevated on scheduled news days, such as earnings news. In the recent sample, a typical day with AHT earnings news is more than twice as volatile compared to RTH (see Table I). Notably, trading activity more than tripled in the post-2018 sample on days with insider trader news with substantial trading volume.[16]

[16]In Internet Appendix Table B.1 we show that AHT returns, volatility, and next-day returns reflect the AHT news sentiment.

IV. Retail Access to After-Hours Trading

So far, we have documented that trading is more costly (e.g., higher spreads) for liquidity takers and potentially risky for liquidity providers as AHT news arrives. Good (bad) news creates buying (selling) opportunities during AHT. However, faster access to news can generate adverse selection (Foucault et al., 2016; Hoffmann, 2014), especially for retail investors who can mainly provide liquidity during AHT. We next explore whether after-hours firm-specific news attracts retail investors. 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 a simple proxy for 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.[17] Robinhood is a retail brokerage firm that provides information on retail 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, 2025; Welch, 2022). For example, Welch (2022) shows that retail investors 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

[17]For details about the platform see, for example, Barber et al. (2022), Eaton et al. (2022), Welch (2022) and Fedyk (2025).

by retail investors. Jones et al. (2025) 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) 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 4:00 p.m. to 6:00 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:

$$Pop_{i,t}^{AHT} = \alpha_i + \gamma_t + \beta_1 RH_t^{AHT} + \beta_2 news_{i,t}^{AHT} + \beta_3 RH_{i,t}^{AHT} \times news_{i,t}^{AHT} + \epsilon_{i,t} \qquad (1)$$

The dependent variable $Pop_{i,t}^{AHT}$ is the absolute value of the change in the number of Robinhood user holdings between 4:00 p.m. and 8:00 p.m. of stock i on day t, 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, equal to 1 if non-neutral firm-specific news is announced only during after-hours trading (AHT), and 0 if no news or neutral news is announced during AHT and RTH. RH_t^{AHT} x $News_{i,t}^{AHT}$ is the interaction term between RH_t^{AHT} and $News_{i,t}^{AHT}$.[18] We also include Good News (Bad News), which is defined as the accumulated adjusted RavenPack news sentiment score between 4:00 p.m. and 8:00 p.m. 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. We include time (Weekday) and firm fixed effects in the specification.

[Table IV about here.]

Table IV shows the results for Robinhood popularity across different news types. Our

[18]Internet Appendix Figure H.1 provides visual evidence to support the DiD parallel trend assumption.

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.[19] 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.[20] 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" (Barber et al., 2022; 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. (2024) 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.4. Four variables are from CRSP daily files, 20 variables are from WRDS Intraday Indicators, and we construct the remaining 13 variables (plus the five variables at the venue level) using the TAQ data.

[19] A back-of-the-envelope calculation, based on the average account size of $3,500, an average holding of 3 stocks (Fedyk, 2025; Welch, 2022), and an average of 112 firm-specific news events per day, suggests that a coefficient of 1.798 per stock-day implies around $234k ($59 million) per day (year) entering the platform on AHT news days.

[20] 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.

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 4:00 p.m. and 8:00 p.m. from May 3, 2018, to August 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 ability to offer ranking of feature importance (Hastie et al., 2017). These rankings are instrumental for comprehending the influence of explanatory variables on target variables in our setting.

Panel A of Figure 2 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.[21] It contributes more than half (55.96%) 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 (10.32%) 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 2, replacing the total buyer-

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

initiated odd-lot trades with the buyer-initiated odd-lot trades at venue levels, we see that Cboe EDGX, followed by FINRA, stands out as the exchange where these trades are initiated. This result is interesting since Cboe EDGX offers priority to its retail customers, and it seems to be one of the preferred destinations for order routing of non-marketable limit orders through wholesalers such as Citadel. The fact that FINRA appears as the second important feature is in line with Robinhood's SEC 606 disclosures of non-directed orders sent to wholesalers.

[Figure 2 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. Panel A of Figure 3 illustrates the average Robinhood popularity and RTI forecasts based on the full RF model, including 42 explanatory variables. It shows that the out-of-sample RTI forecasts are very close to the actual popularity measures with a correlation of 90%. Panel B of Figure 3 shows the RTI forecats based on a univariate RF model that includes the most important feature, that is, buyer-initiated odd lot trades on Cboe EDGX, as the single explanatory variable. The parsimonious model performs fairly well, with a correlation of 76%.[22]

[Figure 3 about here.]

As a comparison, we repeat the same analysis using data only from RTH. The results in Internet Appendix Figure C.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.

[22]We have repeated the same forecasting exercise with a linear univariate model and obtain a correlation of 73%, confirming the information content of buyer-initiated odd lot trades on Cboe EDGX.

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 Cboe EDGX, 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 4 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 4 about here.]

We first observe that FINRA (ADF) which attracts the largest dollar volume (see Panel A of Figure 1) 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 4) 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 equal to 1 if non-neutral firm-specific news is announced only during after-hours trading (AHT), and 0 if no news or neutral news is announced during AHT and RTH. 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 5 about here.]

The figure shows that AHT news triggers buyer-initiated odd-lot trades across venues, posing a challenge for the identification of a simple proxy for retail participation, a concern we address in the next section.[23]

D. Robinhood Extension of AHT hours

On Mar 29, 2022, the Robinhood platform extended the trading hours for all traders from 4:00–6:00 p.m. to 4:00–8:00 p.m. (Mantel and Saglam, 2024). Suppose the odd-lot trades on Cboe EDGX 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 the 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:

[23] In Internet Appendix Section D, we show the results of two-way fixed effects regressions for different types of news. The average number of odd-lot trades sorted by firm characteristics (price and size) across venues reported in Internet Appendix E, reflects a similar identification challenge.

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

The dependent variable $y_{i,t}$ is the total buyer-initiated (Panel A) and seller-initiated (Panel B) odd-lot trades from 6:00 p.m. to 8:00 p.m. (normalized by the trades from 4:00 p.m. to 6:00 p.m.) of stock i on day t (as well as trades at each venue, i.e., Cboe EDGX, 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 equal to 1 if non-neutral firm-specific news is announced only during after-hours trading (AHT), and 0 if no news or neutral news is announced during AHT and RTH. We include time (Weekday) and firm fixed effects in the specification.[24]

[Table V about here.]

In Table V, 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 half (from 6:00 p.m. to 8:00 p.m.) of AHT relative to the first half (from 4:00 p.m. to 6:00 p.m) increase significantly on Cboe EDGX and NYSE, while we see a significant decline on NASDAQ. The latter could reflect the migration of odd-lot trades from NASDAQ to Cboe EDGX (and NYSE) once the trading constraint is relaxed. Firm-specific news is often released in the first half of AHT, so we see a significant decline only in buyer-initiated odd-lot trades on Cboe EDGX 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 EDGX 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 EDGX odd-lot trades are a good proxy for retail participation

[24]Internet Appendix Figure H.2 provides visual evidence to support the DiD parallel trend assumption.

in AHT on firm-specific news days.

V. Retail Liquidity Provision

For retail investors, who are mostly limited 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 investors benefit from retail priority in liquidity provision when more sophisticated traders can exploit low-latency technology to react to public news.

A. Stock Returns and Retail Participation

Short-term return dynamics contain important information about the trading motives of liquidity providers (Glosten and Milgrom, 1985; Campbell et al., 1993). For example, short-term return reversals are often associated with compensation for uninformed liquidity provision (Nagel, 2012). We first test whether there is any evidence of return reversal between AHT returns and next-day intraday returns, and the effect of retail liquidity provision on the reversals. In particular, we run panel regressions of the next-day returns on AHT returns, the retail trading proxy we introduced in Section IV.B, and their interaction. We repeat the same analysis for the sub-samples of news versus no-news days. We focus on the post-2018 period when we observe increased retail participation.

$$r_{i,t+1} = \gamma_t + \beta_1 r_{i,t}^{AHT} + \beta_2 RT_{i,t}^{AHT} + \beta_3 r_{i,t}^{AHT} \times RT_{i,t}^{AHT} + controls + \epsilon_{i,t+1} \tag{4}$$

The dependent variable $r_{i,t+1}$ is the next day open-to-close return of the stock i on day t. $r_{i,t}^{AHT}$ is the AHT return measured by the price change between 4:00 p.m. and 8:00 p.m. The retail trading proxy $RT_{i,t}^{AHT}$ is captured by the Robinhood retail popularity between August 1, 2018, and August 13, 2020, and by the RTI forecasts between August 14, 2020

and October 31, 2022.[25] AHT news days are identified when non-neutral firm-specific news is announced only during AHT. On no-news days, either no news or neutral news is announced during AHT and RTH. We include time fixed effects and control for the AHT return sign and AHT volume in the specification. We double-cluster standard errors by firm and date. We expect the coefficient β_3 on the interaction term to be negative (positive) if the retail trading is uninformed (informed) (Bogousslavsky et al., 2024).

[Table VI about here.]

The column (1) of Table VI shows a mild short-term reversal between AHT returns and next-day intraday returns in a univariate specification, in line with the tug of war literature arguing overnight price anomalies driven by noise trading (Lou et al., 2019; Akbas et al., 2022). AHT retail trading activity predicts significantly negative returns the next day, only on days with AHT news. The significantly negative β_3 in all specifications indicates the contribution of retail investors to return reversals. The higher magnitude of β_3 on days without news reflects the limited liquidity on those days. Controls for general trading activity (AHT volume) and potential asymmetric effects (return sign) on reversals do not change the conclusion.

B. AHT Liquidity and Retail Participation

Next, we continue with an analysis of the interaction between retail trading and market liquidity, especially on the days of AHT news releases. In particular, we run panel regressions of liquidity measures, that is, quoted spread, effective spread, and its components, realized spread and price impact, on the retail trading proxy, after-hours (earnings) news dummy, and their interaction.

[25] In Online Appendix Table F.1, we report the results using only the subsample between August 1, 2018, and August 13, 2020, where we observe Robinhood retail popularity. In Online Appendix Table G.1 we report the results using the number of odd-lot trades on the Cboe EDGX as a proxy for Robinhood retail popularity between May 3, 2018, and October 31, 2022. We obtain similar results.

$$y_{i,t} = \alpha_i + \gamma_t + \beta_1 RT_{i,t}^{AHT} + \beta_2 news_{i,t}^{AHT} + \beta_3 RT_{i,t}^{AHT} \times news_{i,t}^{AHT} + \epsilon_{i,t} \quad (5)$$

The dependent variable $y_{i,t}$ is a liquidity measure of the stock i on day t. The retail trading proxy $RT_{i,t}^{AHT}$ is captured by the Robinhood retail popularity between May 3, 2018, and August 13, 2020, and by the RTI forecasts between August 14, 2020 and October 31, 2022.[26] $News_{i,t}^{AHT}$ in Panel A ($Earnings_{i,t}^{AHT}$ in Panel B) is a dummy variable equal to 1 if non-neutral firm-specific (earnings) news is announced only during after-hours trading (AHT), and 0 if no news or neutral news is announced during AHT and RTH. We include time and firm fixed effects in the specification and cluster error at the firm level.

[Table VII about here.]

The panel regressions reported in Table VII reveal interesting observations. We first see that an increase in AHT retail activity is associated with a significant reduction in spreads. The increase in liquidity might be driven by retail liquidity provision, but it is also possible that retail activity coincides with the trading of other, possibly faster, liquidity providers. This setting does not allow us to draw a strong causal conclusion. Narrower quoted spreads on AHT news days, along with wider effective and realized spreads, as well as larger price impact, indicate increased costs for liquidity demanders and higher revenues for liquidity providers as a result of information arrival. However, the coefficient of the interaction term for all spread measures is positive, indicating the potential for picking-off risks due to informational or speed advantages. The negative coefficient on the price impact, along with the evidence from the return reversals, suggests that the latter is a more plausible explanation. We repeat the same analysis on the days of earnings news releases, reported in Panel B of Table VII. The results are similar, except that the coefficient on the interaction term for effective spread is not significant. This suggests that trading is

[26] In Online Appendix Table F.2 we report the results using only the subsample between May 3, 2018, and August 13, 2020 where we observe Robinhood retail popularity. In Online Appendix Table G.2 we report the results using the number of odd-lot trades on Cboe EDGX as a proxy for Robinhood retail popularity between May 3, 2018, and October 31, 2022. We obtain similar results.

less costly for liquidity demanders, thereby increasing the likelihood of picking-off risk for liquidity providers on days with AHT earnings news. Although a positive coefficient on the realized spread suggests increased revenues for liquidity suppliers, it is not obvious whether the retail investors are the ones that benefit from it (Barrot et al., 2016).

C. Introduction of Cboe EDGX Retail Priority

To uncover a causal relationship between AHT retail activity and liquidity provision, we now examine the relationship between profits and liquidity provision around the introduction of the retail priority rule on Cboe EDGX 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 Cboe EDGX allows retail investors to jump the queue, that is, the price-retail-time priority. This feature levels the playing field for retail investors against traders with low-latency technologies. However, at the same time, it poses the danger of exposing retail investors to picking-off risk around news arrivals unless retailers constantly monitor the market and have the capacity for fast cancellations in case of unexpected price moves (Khomyn and Putniņš, 2021; Copeland and Galai, 1983). This risk is particularly high for volatile stocks, but also for stocks with high book depth when retail priority pushes retail orders in front of the queue.

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

$$y_{i,t} = \alpha_i + \gamma_t + \beta_1 RP^{EDGX}_{t,int} + \beta_2 Earnings^{AHT}_{i,t} + \beta_3 RP^{EDGX}_{t,int} \times Earnings^{AHT}_{i,t} + \epsilon_{i,t} \quad (6)$$

The dependent variable $y_{i,t}$ is the average realized spread around the buyer-initiated odd-lot trades from 4:00 p.m. to 8:00 p.m. of stock i on day t (as well as trades at each venue, i.e., Cboe EDGX, 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 equal to 1 if non-neutral firm-specific earnings news is announced only during after-hours trading (AHT), and 0 if no news or neutral news is announced during AHT and RTH. We include time (Weekday) and firm fixed effects in the specification.[27]

[Table VIII about here.]

We report the results in Table VIII. We focus on the interaction term, which shows the effect of introducing retail priority on the Cboe EDGX on profits from liquidity provision on days with AHT earnings news. We find a significant reduction in realized spreads only on Cboe EDGX, providing compelling evidence of an adverse effect of retail priority on liquidity provision. When we split the sample by AHT return volatility (measured by absolute returns) and quoted depth (measured by shares at the best ask), Panels B and C show that the effect is concentrated among stocks with both high AHT volatility and high quoted depth. These findings are consistent with heightened adverse selection risk faced by retail liquidity providers when prices adjust rapidly in the presence of substantial displayed depth.

D. A Tale of Two Events

We also provide microscopic evidence on intraday AHT liquidity provision around two events: i) Apple's (AAPL) earnings news on July 30, 2020, at 4:30 p.m., which attracted the

[27] Internet Appendix Figure H.3 provides visual evidence to support the DiD parallel trend assumption.

highest Robinhood popularity on an earnings announcement day in the Robintrack sample[28] and ii) Gamestop (GME) frenzy on January 26, 2021, triggered by Elon Musk's tweet "Game-Stonk" at 4:08 p.m. This analysis allows us to compare the reaction of market participants on different exchanges to scheduled and unscheduled events.

D.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 4:30:00 p.m. 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 6).

[Figure 6 about here.]

Figure 6 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 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 a rapid reaction to the news, with the highest increase in the quote and trades on NASDAQ, with ask prices mostly in line with the post-event price, suggesting that NASDAQ drives the price discovery process

[28] When we include only the news that is released after 4:10 p.m. to allow sufficient time for the pre-event window.

followed by market participants on other exchanges.[29] In other words, on the news days when retail investors are active, there are sophisticated traders with low-latency technology, and the price path is consistent with uninformed liquidity provision as illustrated in Gregoire and Martineau (2022).

D.2. GameStop Tweet

The GameStop saga, which started in January 2021, took a new turn when Elon Musk tweeted at 4:08 p.m. on January 26, 2021, with a link to a bullish view on Reddit's Wallstreetbets. It 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 7 about here.]

Figure 7 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 and a jump in trades with a temporary price move, after-hours trading became active only a few minutes later. 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 (Brogaard et al., 2019; Foucault et al., 2016; Hoffmann, 2014).

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

VI. Portfolio Analysis

We have demonstrated so far that trading AHT, in particular, providing liquidity around AHT news releases, is not a profitable strategy for retail investors, despite the large bid-ask spreads. Trading AHT exposes retailers to adverse selection risk in the form of picking off risk due to the stale nature of retail orders (sitting ducks). Although retail traders might incur losses individually, there might be some wisdom in the aggregate Robinhood investors observed in their aggregated consensus portfolios, as demonstrated by Welch (2022) and Fedyk (2025). In the final section, we assess whether news-driven AHT participation is a wise strategy for the Robinhood crowd.

We follow the recent literature (Fedyk, 2025; Van der Beck and Jaunin, 2025; Welch, 2022) and construct a similar Robinhood representative portfolio (ARH^{RTH}), assuming each investor allocates the same dollar amount in the stock. The weight of a stock i at time t in the portfolio is computed as follows:

$$w_{i,t}^{RTH} = \frac{RH_{i,t}^{RTH}}{\Sigma_i RH_{i,t}^{RTH}} \tag{7}$$

where $RH_{i,t}^{RTH}$ is the number of Robinhood investors holding the stock i at time t at the end of the regular trading hours (at 4:00 p.m.). As before, we only include the constituents of the S&P 1500 index in the investment opportunity set, and use the S&P 1500 index as the market portfolio (MRK^{SP1500}). For the Robinhood sample, between 3 May 2018 and 13 August 2020, we use the retail investor holdings obtained from Robintrack.

We contrast both benchmarks (ARH^{RTH}, MRK^{SP1500}) with a news-driven AHT retail portfolio (ARH^{RTH}) with the following weights:

$$w_{i,t}^{ATH} = \frac{Pop_{i,t}^{AHT}}{\Sigma_i Pop_{i,t}^{AHT}} \tag{8}$$

where $Pop_{i,t}^{AHT}$ is the absolute value of the change in the number of Robinhood user holdings

between 4:00 p.m. and 8:00 p.m. of stock i on day t. The retail investor only considers a stock for the portfolio if there is a firm-specific AHT news on day t. A stock is included in the retail investor's portfolio only when firm-specific AHT news occurs on day t.[30] During the sample period, an average of 112 unique firm-specific news events take place per day, implying a daily investment universe of approximately 112 stocks. The portfolio weights reflect the retail traders' attention to firm-specific AHT news. Note that this strategy has a high portfolio turnover and, therefore, is costly to implement. We abstract from transaction costs in our analysis. We compute daily stock returns, portfolio weights (daily rebalancing), and compound returns to assess performance over time. We extend the analysis until October 31, 2022, by using the RTI measure we obtained from the random forest (RF) algorithm described in Section IV.B.

Figure 8 shows the cumulative return performance of the benchmark Robinhood representative portfolio (ARH^{RTH}), the market portfolio (MRK^{SP1500}) and the news-driven AHT retail portfolio (ARH^{AHT}), both for the Robinhood sample from May 3, 2018, to August 13, 2020 (vertical line) and the extended predicted sample until October 31, 2022.

[Figure 8 about here.]

We observe the superior performance of (ARH^{RTH}) toward the end of the Robinhood sample, consistent with Welch (2022) and Fedyk (2025), albeit less pronounced, because our cross-section is limited to relatively larger firms, only constituents of the S&P1500 index. The performance gap widens in the prediction sample, in line with the wisdom of Robinhood crowd evidence. However, ARH^{AHT} tells an entirely different story: news-driven AHT retail strategy underperforms both benchmarks and yields a negative cumulative return. This suggests that AHT retail participation is distinct from RTH retail activity and is not profitable for retail investors. Regression results reported in Table IX confirm these findings

[30] In Online Appendix J, we show the performance of alternative AHT retail portfolios, excluding news restriction (Figure J.1), weights based on AHT Robinhood user holdings rather than popularity (Figure J.2) and weights based on the share method, each Robinhood investor representing one share in each stock in the portfolio (Figure J.3). Our conclusion is not sensitive to these choices.

using both a one-factor (CAPM) model and a six-factor model that includes market, size, value, profitability, investment, and momentum factors.

[Table IX about here.]

VII. Conclusion

This paper documents new evidence on the microstructure of the after-hours market on U.S. trading venues. Although trading activity in AHT is generally only a fraction of the RTH activity, AHT is elevated on days with firm-specific news. Our analysis reveals that the landscape of AHT has changed substantially, especially in the last few years, with the entry of zero-commission platforms, 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 6:00 p.m. in 2018 and extending the hours until 8:00 p.m. 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. 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.

We identify odd-lot trades, originating from Cboe EDGX, with retail priority as the key indicator of AHT retail activity. Although this priority is valuable for liquidity providers in the event of competition for liquidity provision, it exposes retail investors to picking-off risk by low-latency traders, especially on days with earnings news releases. One limitation of our proposed measure is that it captures retail trades exclusively from a single broker—Robinhood. Consequently, it may not reflect variations in AHT execution quality for non-marketable limit orders across different brokers, similar to the differences recently documented for market orders (Schwarz et al., 2025). Therefore, we need more information

on execution quality in after-hours markets. Transparency on AHT in SEC 606 disclosures would be a step in the right direction. We also need a better theoretical understanding of the retail priority rule in the context of transparency and adverse selection. For example, could it be implemented in hidden markets (e.g., Cboe BZX platform) to protect retail investors against picking-off risk without sacrificing much execution probability? Given the inferior performance of AHT retail trading activity, retail brokerage firms should provide more educational resources on managing risks related to AHT, especially for first-time investors who might suffer from the primacy effect in stock market participation (Arikan et al., 2019). They also need to reconsider AHT order submission and routing choices, given the sustained increase in retail trading activity (The Economist, 2025).

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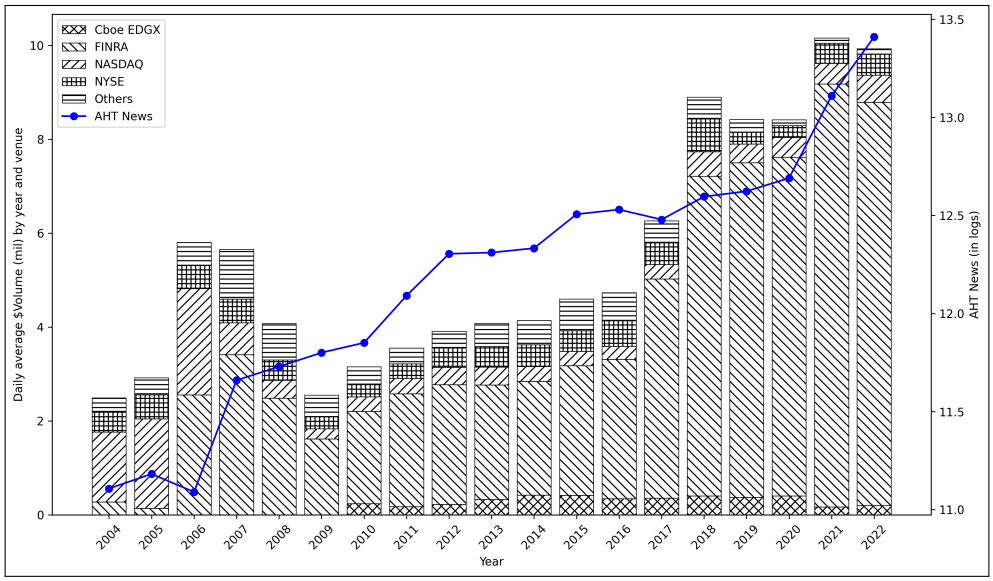
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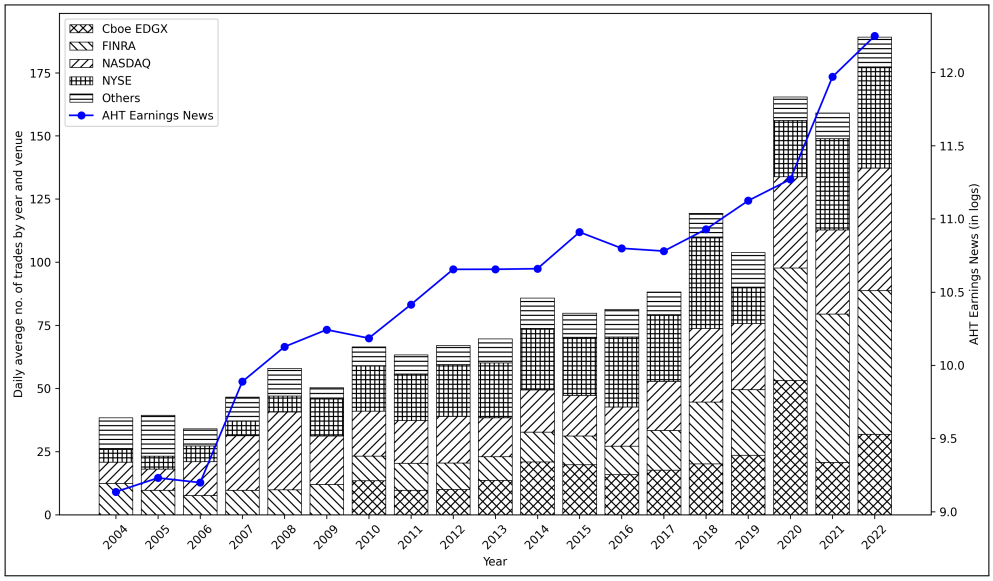
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Figure 1. AHT News and Trading over Time

(a) AHT News and Dollar Trading Volume by Venue



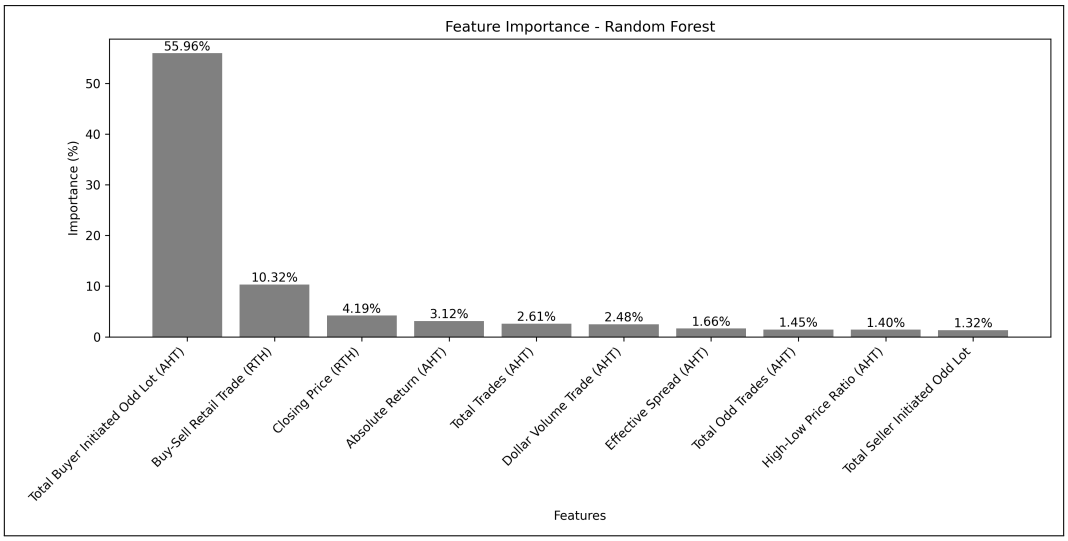
(b) AHT Earnings News and Number of Trades by Venue



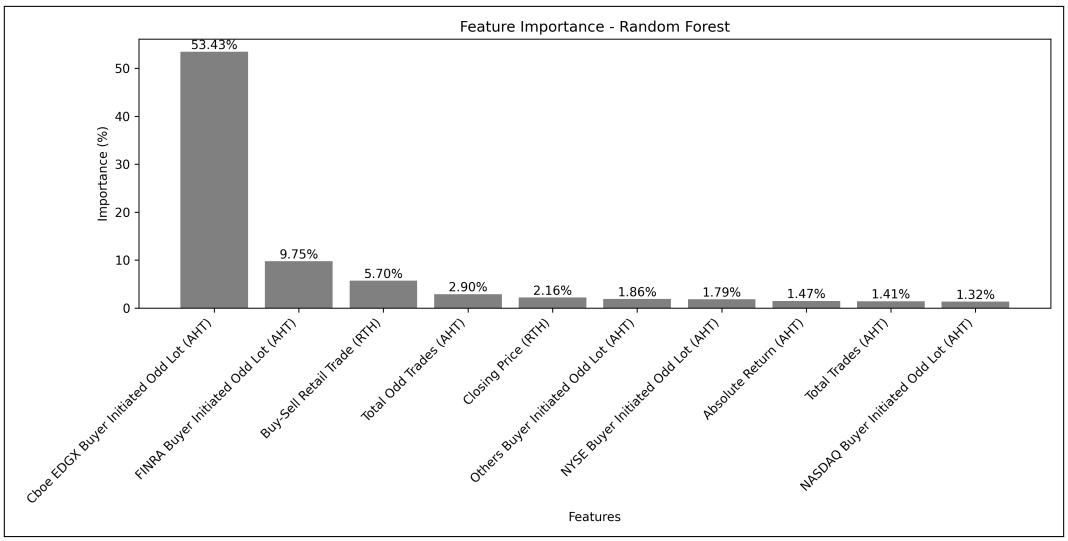
The figure plots the time series of the dollar trading volume (Panel A) and daily average number of trades (Panel B) for S&P 1500 stocks in the after-hours market, during the period January 5, 2004, to October 31, 2022. The daily average number of trades and dollar volume (in millions) are averages across all stocks and trading platforms in a year. The trading venues include the Cboe EDGX, platforms that report to the FINRA alternative display facility (ADF), NASDAQ, NYSE, and other smaller trading platforms. The blue solid line in Panel A (Panel B) indicates the natural logarithm of the number of all (earnings) news from RavenPack disseminated during AHT per year for S&P 1500 stocks. After-hours trading (AHT) refers to the trading session from 4:00 p.m. to 8:00 p.m.

Figure 2. Random Forest Algorithm

(a) Feature Importance



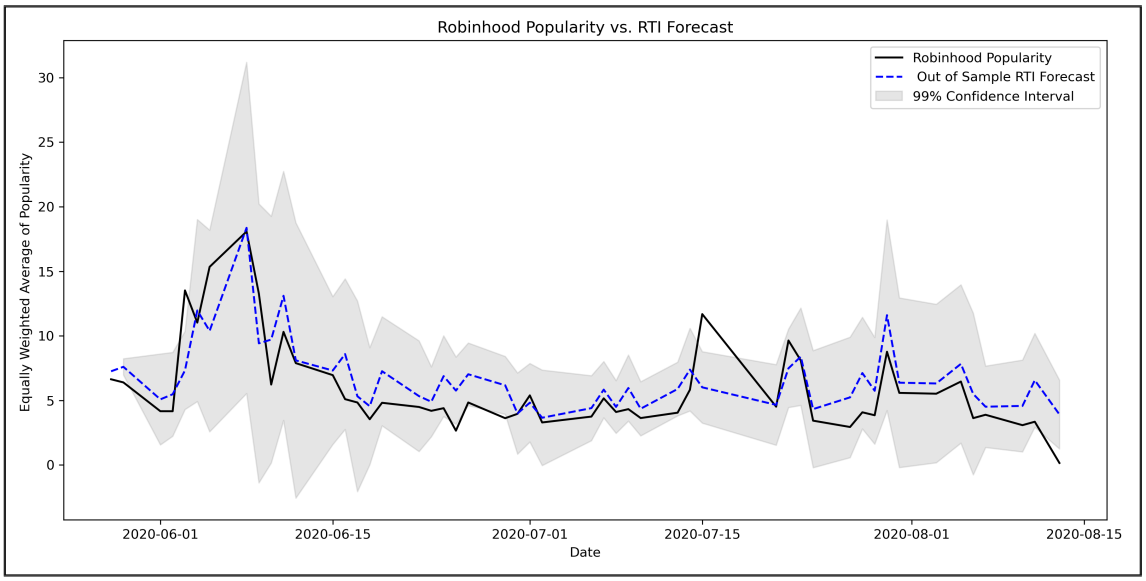
(b) Feature Importance - By Venue



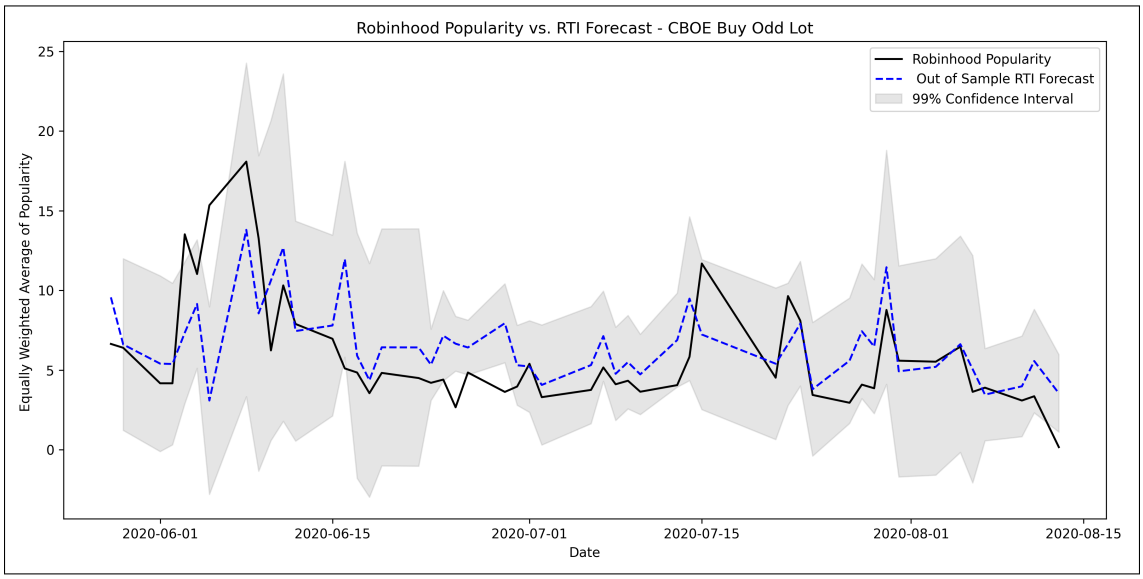
This figure ranks features by their importance according to Random Forest's internal procedure that ranks features based on the total reduction in Gini impurity (a default option that aggregates the importance of each feature across all splits where the feature was used). The target variable is the absolute value of the difference in the number of users holding S&P 1500 constituents on Robinhood for each day between 4:00 p.m. and 8:00 p.m. In Panel B, the trading venues include Cboe EDGX, 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 (42) explanatory variables, i.e., features, in Panel A (Panel B). They are defined in Internet Appendix Table A.1.

Figure 3. Robinhood Popularity Forecast

(a) RTI Forecast - Full Model



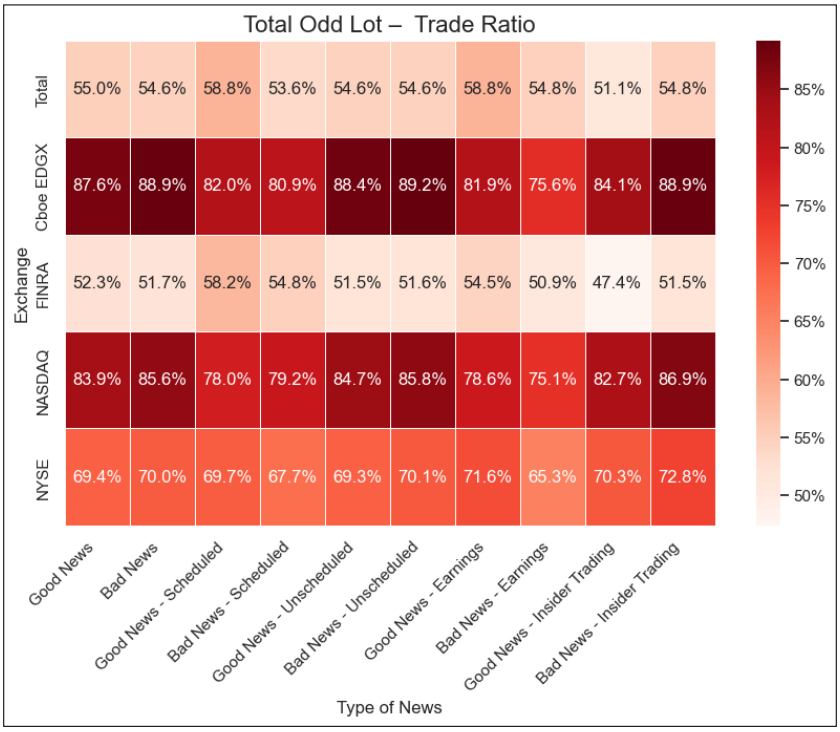
(b) RTI Forecast - Univariate Model



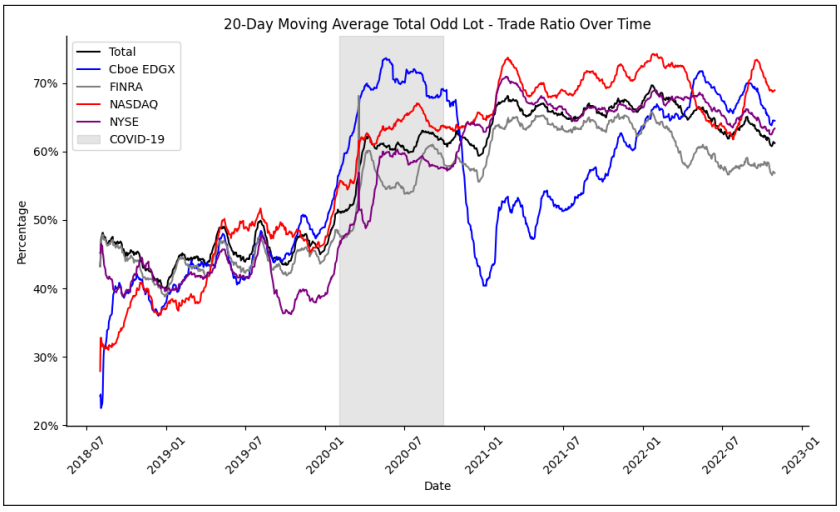
This figure shows the out-of-sample predicted and actual values of the absolute value of the difference in the number of users holding S&P 1500 constituents on the Robinhood platform for each day between 4:00 p.m. and 8:00 p.m. We use the random forest algorithm, full model including 42 explanatory variables (Panel A), and univariate model including only buyer-initiated odd lots on Cboe EDGX (Panel B), 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 4. Odd-lot Trades

(a) Heatmap

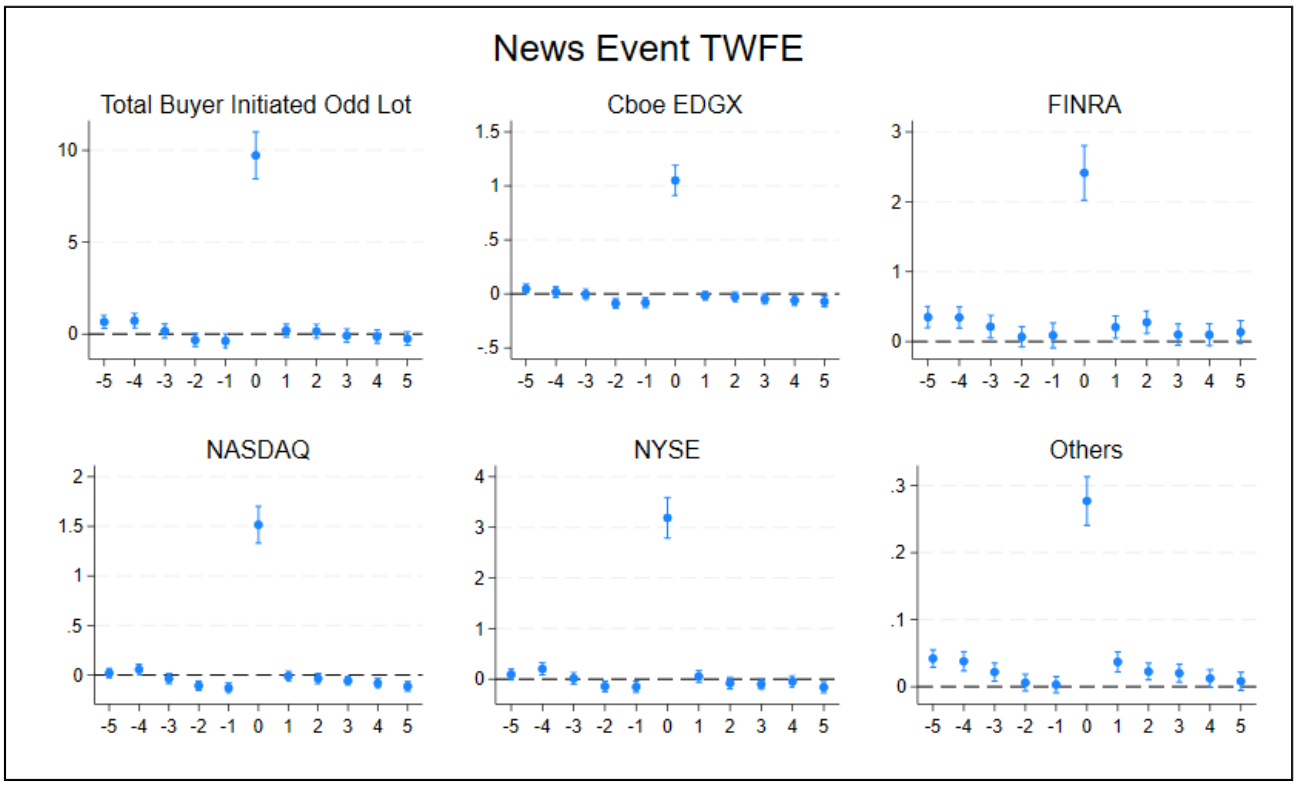


(b) Odd-lot to Total Trade over Time



This figure shows the ratio AHT odd-lot trades to the total number of trades across venues. Panel A shows a 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 (20-day moving average of) 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, platforms that report FINRA alternative display facility (ADF), NASDAQ and NYSE.

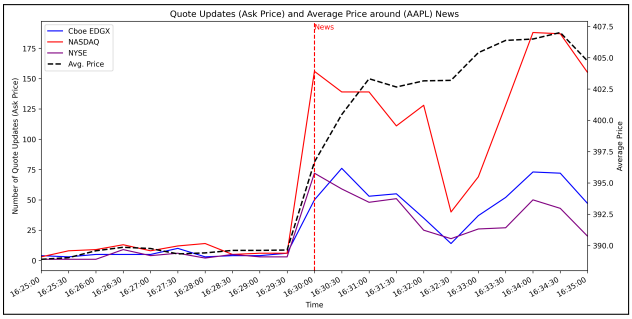
Figure 5. News Days



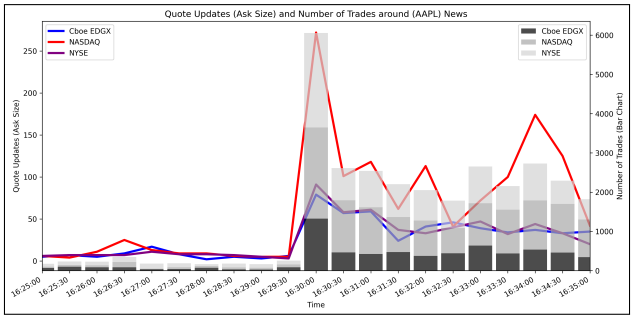
This figure shows the results of the two-way fixed effects model (Equation 2) around news days. The sample covers from August 1, 2018, to October 31, 2022. The trading venues include the Cboe EDGX, platforms that report to the FINRA alternative display facility (ADF), NASDAQ, NYSE, and other smaller exchanges.

Figure 6. Apple Earnings News

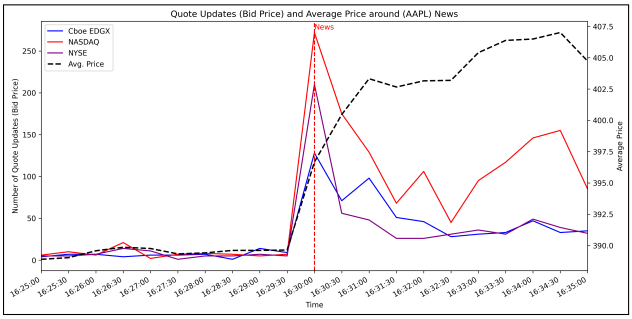
(a) Ask Price



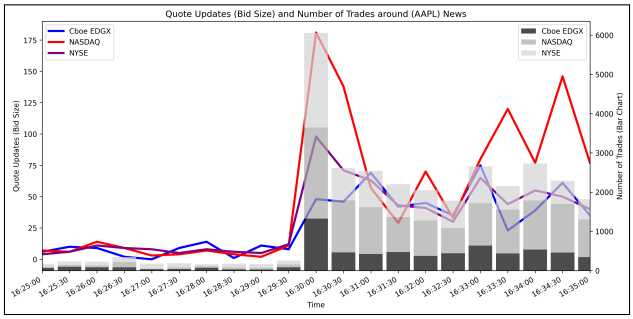
(b) Ask Size



(c) Bid Price



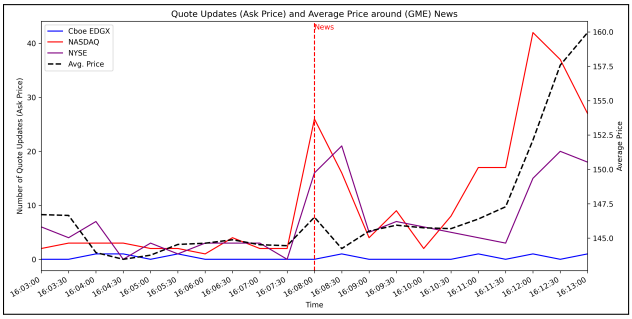
(d) Bid Size



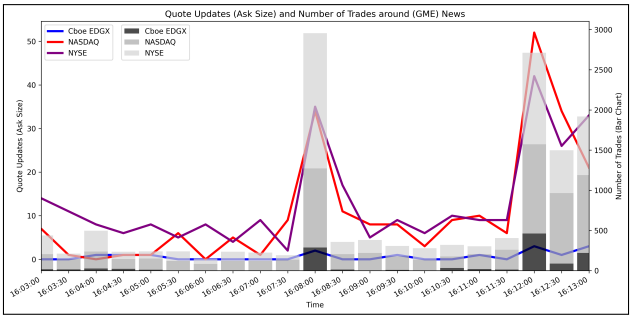
This figure shows the quote updates on different exchanges around Apple's earnings news on July 30, 2020. We report the number of quote updates within 30-second intervals that improve the best (ask and bid) price and the number of quote updates that increase the BBO depth both at the best bid and ask levels. We also report the average transaction price and the number of trades initiated on each exchange within 30-second intervals. The event occurred at 4:30 p.m., 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.

Figure 7. GameStop Tweet

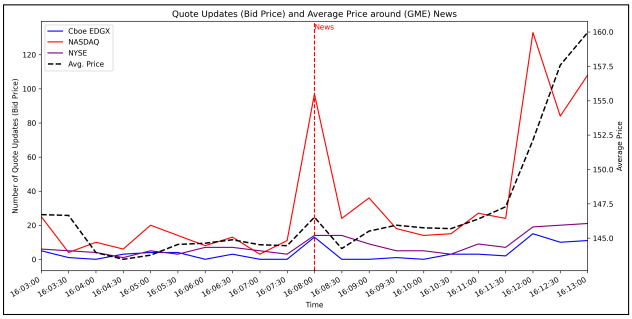
(a) Ask Price



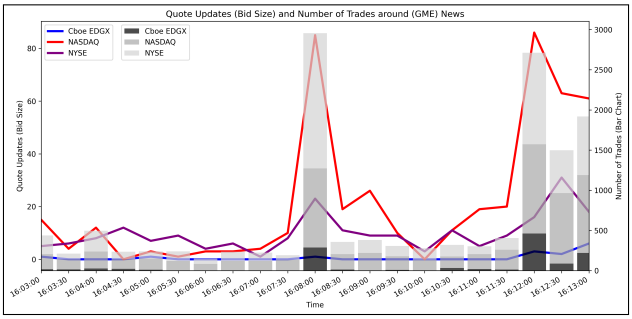
(b) Ask Size



(c) Bid Price

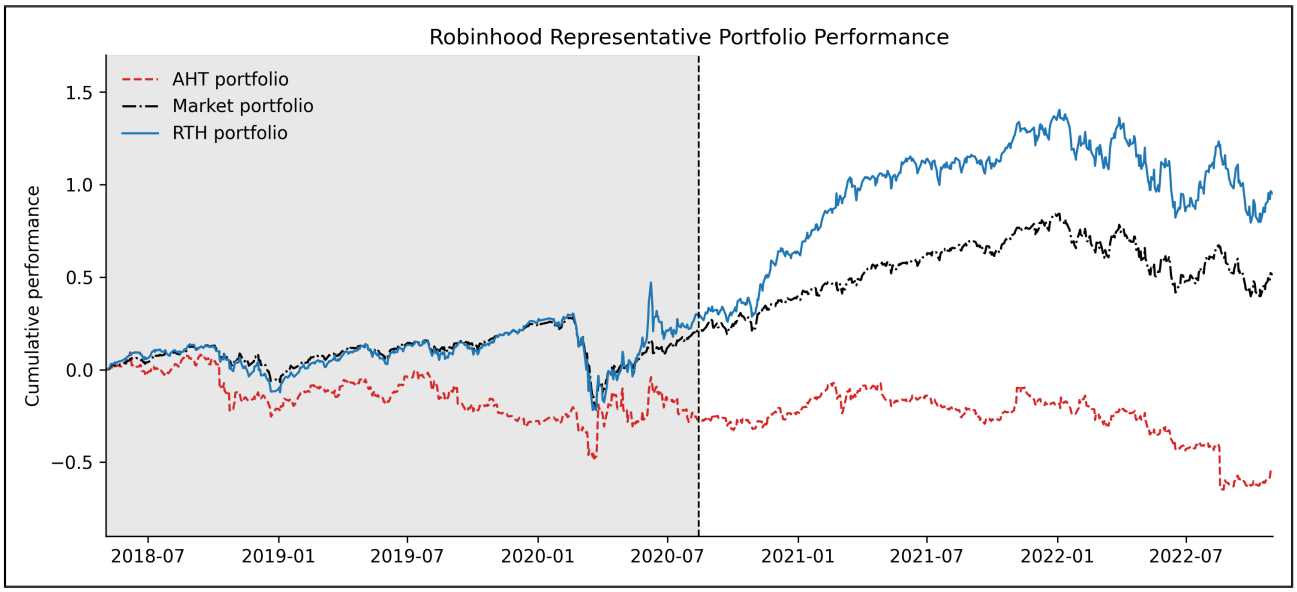


(d) Bid Size



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 4:08 p.m., 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.

Figure 8. Portfolio Analysis



This figure shows the cumulative return performance of the benchmark Robinhood representative portfolio (ARH^{RTH}), the market portfolio (S&P 1500) and the news-driven AHT retail portfolio (ARH^{AHT}), both for the Robinhood sample from May 3, 2018, to August 13, 2020 (vertical line) and the extended predicted sample until October 31, 2022.

Table I Summary statistics

The table presents return, volatility (measured by absolute return), trading activity (e.g., number of trades and dollar volume), BBO depth, which is calculated as the average number of shares quoted at the best bid and offer prices, 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 9:30 a.m. to 4:00 p.m. After-hours trading (AHT) refers to trading sessions from 4:00 p.m. to 8:00 p.m.

Panel A. Equally-Weighted Average							
Panel A.1. RTH	Mean	Std. Dev.	P5	P25	Median	P75	P95
Return	1.65	232.87	-327.53	-97.52	0.00	99.60	327.27
Volatility	148.55	179.34	7.96	43.29	98.59	191.40	447.76
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
BBO depth	3,357.95	70,000.72	166.52	309.09	534.37	1,157.11	7,767.64
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
Return	1.32	158.03	-60.26	0.00	0.00	0.00	67.11
Volatility	23.74	156.25	0.00	0.00	0.00	12.89	119.41
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
BBO depth	577.23	943.67	100.04	181.53	305.35	560.24	1,900.00
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
Return	1.07	172.71	-254.03	-76.59	2.31	80.32	246.95
Volatility	114.31	129.47	6.73	35.06	78.51	149.43	335.94
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
BBO depth	9,543.87	178,592.00	162.16	324.65	796.82	2,478.04	20,395.11
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
Return	1.65	73.66	-55.85	-4.09	0.00	8.10	61.20
Volatility	24.04	69.65	0.00	0.00	6.14	24.88	95.33
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
BBO depth	724.06	1,124.59	106.65	223.93	389.49	725.17	2,413.05
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. take a value of 50 to 100 (0 to 50). A score of 50 represents a neutral sentiment. Regular trading hours (RTH) refer to trading sessions from 9.30 a.m. to 4.00 p.m. After-hours trading (AHT) refers to the trading session from 4:00 p.m. to 8:00 p.m.

	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 average values for the AHT return, volatility measured by absolute return, number of trades, dollar volume, BBO depth, quoted spread, effective spread, realized spread, and the price impact of trades across two sub-samples. Panel A covers the pre-2018 period from January 5, 2004, to July 31, 2018, while Panel B covers the post-2018 period from August 1, 2018, to October 31, 2022. AHT news days are identified when non-neutral firm-specific news is announced only during after-hours trading (AHT). On no-news days, either no news or neutral news is announced during AHT and 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). RTH news is defined as if news is announced only 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 differentiate 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	All	AHT	No-News	Good	Bad	RTH	Scheduled	Unscheduled	Earnings	Insider Trading
Return	0.83	0.90	0.37	5.49	-4.87	1.27	-1.52	1.28	-5.57	-0.25
Volatility	20.83	28.94	18.98	32.67	24.25	21.48	87.64	19.78	205.91	19.58
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
BBO depth	780.55	779.51	654.22	811.57	738.95	1,061.87	996.25	745.67	776.62	395.64
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	All	AHT	No-News	Good	Bad	RTH	Scheduled	Unscheduled	Earnings	Insider Trading
Return	2.91	2.95	3.09	6.18	-0.98	2.75	1.66	3.08	-3.97	1.68
Volatility	29.04	33.75	23.51	36.70	30.16	32.56	110.24	26.57	256.23	27.79
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
BBO depth	480.91	437.88	419.34	456.66	415.01	539.69	628.55	419.98	475.34	663.09
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 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 4:00 p.m. and 8:00 p.m. We use the first observation between 4:00 p.m. and 5:00 p.m. and the last observation between 7:00 p.m. and 8:00 p.m. If data is missing between 7:00 p.m. and 8:00 p.m., we calculate the difference using the last available data point between 6:00 p.m. and 7:00 p.m. If this is also missing, we use the last data point between 5:00 p.m. and 6:00 p.m. 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 equal to 1 if non-neutral firm-specific news is announced only during after-hours trading (AHT), and 0 if no news or neutral news is announced during AHT and RTH. Good News (Bad News) is defined when the accumulated adjusted RavenPack news sentiment score between 4:00 p.m. and 8:00 p.m. takes 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	AHT	Good	Bad	Scheduled	Unscheduled	Earnings	Insider Trading
RH_t^{AHT}	0.298^{***} (8.336)	0.299^{***} (8.201)	0.303^{***} (8.574)	0.335^{***} (5.605)	0.341^{***} (5.719)	0.363^{***} (5.752)	0.467^{***} (5.749)
$News_{i,t}^{AHT}$	0.227 (1.411)	0.530^{***} (2.784)	0.102 (0.476)	2.868^{***} (3.202)	-0.151 (-1.258)	3.992^{***} (2.895)	-0.810^{**} (-1.982)
$News_{i,t}^{AHT} * RH_t^{AHT}$	1.798^{***} (2.644)	2.324^{***} (2.901)	1.363 (1.312)	8.193^{***} (2.076)	0.353^{*} (1.816)	12.055^{**} (2.036)	0.464^{*} (1.752)
Obs.	66,677	63,632	63,123	61,035	65,370	66,248	66,248
Adj. R^2	0.101	0.183	0.088	0.110	0.202	0.108	0.092

Table V DiD Analysis: Robinhood AHT Extension

This table reports the results of the DiD analysis around the Robinhood trading hour extension on March 29, 2022, for S&P 1500 stocks from 4:00–6:00 p.m. to 4:00–8:00 p.m. 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 6:00 p.m. to 8:00 p.m. (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 4:00 p.m. to 6:00 p.m. $RH_{t,ext}^{AHT}$ 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 non-neutral firm-specific news is announced only during after-hours trading (AHT), and 0 if no news or neutral news is announced during AHT and 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	All	Cboe EDGX	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 VI Panel Regressions: Stock Returns

This table reports the results of panel regressions, including stock returns and retail participation. The dependent variable $r_{i,t+1}$ is the next-day open-to-close stock i return on day t. $r_{i,t}^{AHT}$ is the after-hours return calculated as the price changes between 4:00 p.m. and 8:00 p.m. The retail trading proxy $RT_{i,t}^{AHT}$ is captured by the Robinhood retail popularity between August 1, 2018, and August 13, 2020, and by the RTI forecasts between August 14, 2020, and October 31, 2022. News days are identified when non-neutral firm-specific news is announced only during after-hours trading (AHT). On no-news days, either no news or neutral news is announced during AHT and RTH. We include date fixed effects, the AHT return sign and AHT dollar volume as control variables. We double-cluster standard errors by firm and date. We report T-statistics in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	All	All	All	AHT News	AHT News	AHT News	No-News	No-News	No-News
	$r_{i,t+1}$	$r_{i,t+1}$	$r_{i,t+1}$	$r_{i,t+1}$	$r_{i,t+1}$	$r_{i,t+1}$	$r_{i,t+1}$	$r_{i,t+1}$	$r_{i,t+1}$
$r_{i,t}^{AHT}$	-0.015	-0.007	-0.007	-0.005	0.006	0.003	-0.017	-0.007	-0.006
	(-1.359)	(-0.650)	(-0.626)	(-0.341)	(0.411)	(0.189)	(-1.277)	(-0.543)	(-0.470)
$RT_{i,t}^{AHT}$		-0.006***	-0.007***		-0.009***	-0.009***		-0.000	-0.001
		(-3.086)	(-3.235)		(-3.658)	(-3.646)		(-0.056)	(-0.126)
$r_{i,t}^{AHT} \times RT_{i,t}^{AHT}$		-0.033***	-0.033***		-0.064***	-0.064***		-0.375**	-0.371**
		(-3.164)	(-3.119)		(-6.379)	(-6.256)		(-2.465)	(-2.422)
Controls	No	No	Yes	No	No	Yes	No	No	Yes
Observations	1,589,336	1,506,207	1,501,136	134,814	129,594	129,413	1,213,341	1,154,422	1,153,281
Adjusted R^2	0.221	0.223	0.223	0.172	0.175	0.175	0.232	0.235	0.235

Table VII Panel Regressions: Liquidity

This table reports the results of the panel regressions, including liquidity measures and retail participation. The dependent variable $y_{i,t}$ is a liquidity measure of the stock i on day t. The retail trading proxy $RT_{i,t}^{AHT}$ is captured by the Robinhood retail popularity between August 1, 2018, and August 13, 2020, and by the RTI forecasts between August 14, 2020 and October 31, 2022. The variable $News_{i,t}^{AHT}$ is a dummy variable, equal to 1 if non-neutral firm-specific news is announced only during after-hours trading (AHT), and 0 if no news or neutral news is announced during AHT and RTH. We control for time and firm Fixed effects. The sample period is from May 3, 2018, to October 31, 2022. 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.

Panel A. News	Quoted Spread$_{i,t}$	Effective Spread$_{i,t}$	Realized Spread$_{i,t}$	Price Impact$_{i,t}$
$RT_{i,t}^{AHT}$	-0.684***	-0.102***	-0.135***	0.022***
	(-3.566)	(-4.101)	(-4.061)	(3.008)
$News_{i,t}^{AHT}$	-40.866***	6.092***	0.881	4.580***
	(-16.246)	(6.384)	(0.926)	(8.978)
$RT_{i,t}^{AHT}$*$News_{i,t}^{AHT}$	0.574***	0.089***	0.107***	-0.013*
	(3.032)	(3.450)	(3.088)	(-1.711)
Obs.	1,184,859	1,174,449	1,173,592	1,173,592
Adj. R^2	0.515	0.205	0.137	0.007
Panel B. Earnings News				
$RT_{i,t}^{AHT}$	-0.516***	-0.084***	-0.114***	0.017***
	(-4.332)	(-4.926)	(-4.977)	(3.613)
$News_{i,t}^{AHT}$	-57.332***	110.644***	68.497***	32.500***
	(-9.016)	(29.147)	(18.890)	(17.000)
$RT_{i,t}^{AHT}$*$News_{i,t}^{AHT}$	0.477***	0.036	0.074**	-0.021***
	(4.045)	(1.137)	(2.341)	(-4.067)
Obs.	1,184,859	1,174,449	1,173,592	1,173,592
Adj. R^2	0.515	0.206	0.137	0.008

Table VIII DiD Analysis: Cboe EDGX Introduction of Retail Priority

This table reports the results of the DiD analysis around the introduction of the Cboe EDGX 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 variable, equal to 1 if non-neutral firm-specific earnings news is announced only during after-hours trading (AHT), and 0 if no news or neutral news is announced during AHT and RTH. To examine the impact of volatility and book depth on our results, we classify stocks into terciles based on their absolute return and ask depth (in shares) during after-hours trading (AHT) for each trading day. The top tercile represents the stocks with the highest absolute returns and highest depth on the ask side, labelled high-volatility stocks and high depth stocks, respectively. We then repeat the difference-in-differences (DiD) regression analysis separately, 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	All	Cboe EDGX	FINRA	NASDAQ	NYSE
Panel A: Earning News					
$RP_{t,int}^{EDGX}$	-0.000	-0.002***	0.000	-0.001**	-0.001**
	(-1.168)	(-3.089)	(1.117)	(-2.283)	(-2.231)
$Earnings_{i,t}^{AHT}$	0.008***	-0.005*	0.012***	0.000	-0.001
	(4.677)	(-1.876)	(4.319)	(0.131)	(-0.355)
$RP_{t,int}^{EDGX} * Earnings_{i,t}^{AHT}$	0.001	-0.008**	-0.002	-0.001	-0.004
	(0.406)	(-2.271)	(-0.456)	(-0.311)	(-1.149)
Obs.	48,330	8,455	45,506	7,276	6,124
Adj. R^2	0.185	0.362	0.136	0.270	0.386
Panel B: High Volatility Stocks					
$RP_{t,int}^{EDGX}$	-0.001	-0.001	0.000	-0.001***	-0.001***
	(-1.403)	(-1.548)	(0.530)	(-2.656)	(-2.989)
$Earnings_{i,t}^{AHT}$	0.006***	-0.004	0.012***	-0.007***	-0.003
	(3.473)	(-1.459)	(4.332)	(-2.887)	(-1.135)
$RP_{t,int}^{EDGX} * Earnings_{i,t}^{AHT}$	0.000	-0.010**	-0.005	0.001	-0.003
	(0.101)	(-2.455)	(-1.074)	(0.238)	(-0.853)
Obs.	14,459	4,999	13,331	4,380	3,909
Adj. R^2	0.191	0.354	0.148	0.283	0.339
Panel C: High Depth Stocks					
$RP_{t,int}^{EDGX}$	-0.002***	-0.002***	-0.001	-0.000	0.001***
	(-3.436)	(-3.052)	(-0.838)	(-0.477)	(-2.706)
$Earnings_{i,t}^{AHT}$	0.004	-0.003	0.010**	-0.002	-0.002
	(1.494)	(-0.888)	(2.050)	(-0.502)	(-0.587)
$RP_{t,int}^{EDGX} * Earnings_{i,t}^{AHT}$	0.003	-0.011**	0.003	-0.001	-0.005
	(0.643)	(-2.299)	(0.440)	(-0.116)	(-0.936)
Obs.	15,101	4,183	14,009	3,234	2,928
Adj. R^2	0.218	0.336	0.181	0.282	0.382

Table IX Retail Portfolio Performance

The table reports the regression results of the return (net of risk free rate, in percentage) from the Robinhood representative portfolio (ARH^{RTH}) (Panel A) and news-driven AHT retail portfolio on the market factor MKT (CAPM model), as well as 6-factor model, including the size factor SML, value factor HML, profitability factor RMW, investment factor CMA and the momentum factor MOM. We report the results both for the Robinhood sample from May 3, 2018, to August 13, 2022, and the full sample until October 31, 2022. The factors are collected from Kenneth R. French's data library. We report Newey-West t-statistics (in parentheses) using optimal lag selection.

Panel A. Robinhood Representative Portfolio

	Robinhood Period			Full Sample	
	CAPM	6-Factor Model		CAPM	6-Factor Model
alpha	0.014	0.037	alpha	0.026	0.030*
	(0.348)	(1.305)		(1.141)	(1.746)
XMKT	1.240***	1.099***	XMKT	1.176***	1.121***
	(25.902)	(46.984)		(41.372)	(66.173)
SMB		0.172***	SMB		0.315***
		(3.317)			(8.920)
HML		0.189**	HML		0.317***
		(2.191)			(8.233)
RMW		0.199*	RMW		0.023
		(1.847)			(0.524)
CMA		-0.620***	CMA		-0.075
		(-4.629)			(-0.840)
MOM		-0.415***	MOM		-0.189***
		(-3.741)			(-4.701)
R-Squared	81.65%	92.10%	R-Squared	81.41%	91.14%
Observations	546	546	Observations	1,098	1,098

Panel B. News-driven AHT Retail Portfolio

	Robinhood Period			Full Sample	
	CAPM	6-Factor Model		CAPM	6-Factor Model
alpha	-0.069	-0.043	alpha	-0.083	-0.073
	(-0.722)	(-0.424)		(-1.288)	(-1.150)
XMKT	0.997***	0.877***	XMKT	1.000***	0.948***
	(7.522)	(8.647)		(11.896)	(11.711)
SMB		0.416**	SMB		0.393***
		(2.130)			(3.135)
HML		0.221	HML		0.171
		(0.663)			(1.152)
RMW		0.208	RMW		-0.208
		(0.759)			(-1.127)
CMA		-0.728*	CMA		0.015
		(-1.874)			(0.066)
MOM		-0.105	MOM		-0.058
		(-0.463)			(-0.629)
R-squared	33.45%	36.99%	R-squared	28.58%	30.91%
Observations	546	546	Observations	1,097	1,097

Internet Appendix for:

A Pond with Sitting Ducks?
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

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

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 *Quoted Spread* is the time-weighted average of $\textit{Quoted Spread}_s$ computed over all time intervals. For a given stock, the percent effective spread is on the k^{th} trade is defined as

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

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 *Effective spread* is a dollar-volume-weighted average of the $\textit{Effective Spread}_k$ 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

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

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

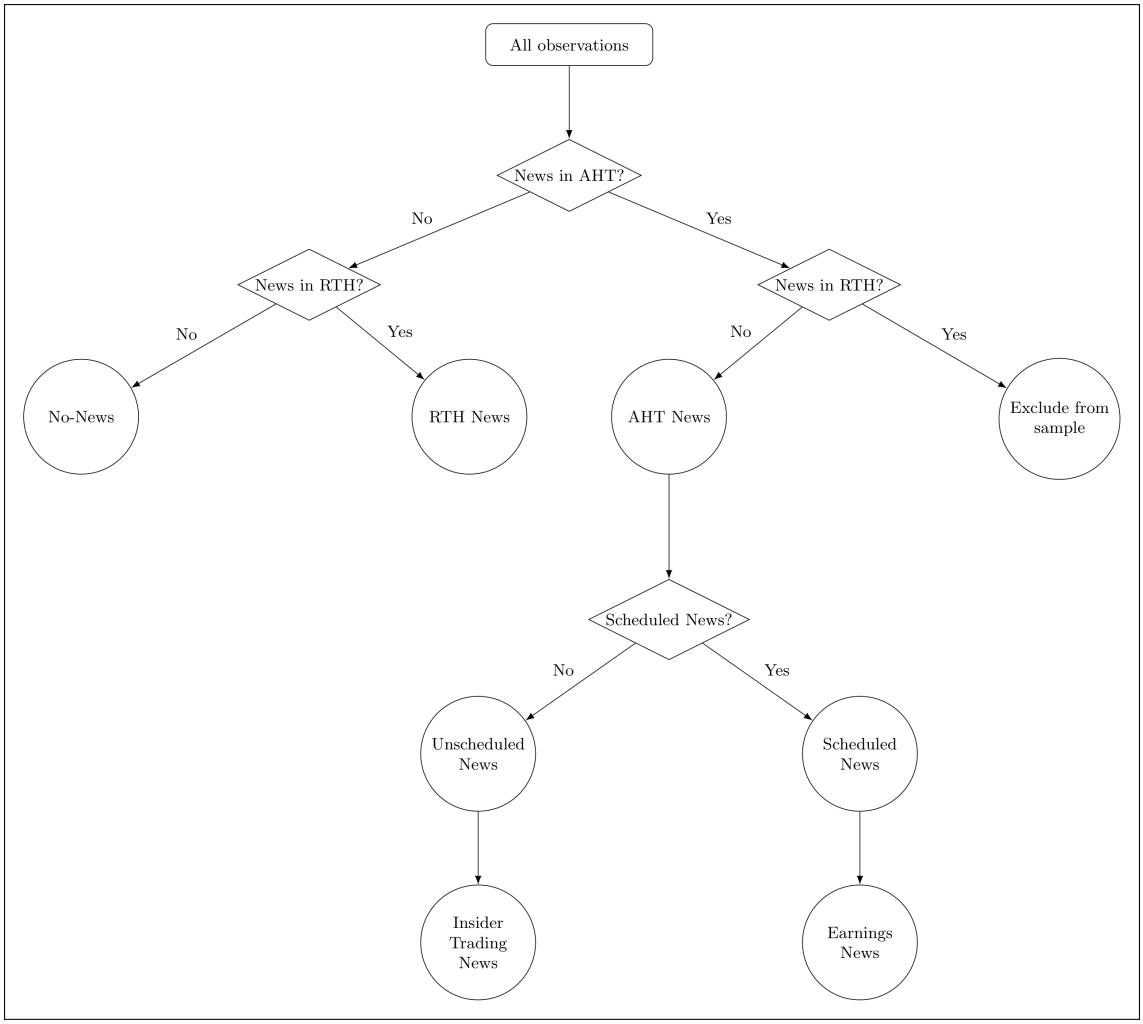
$$\textit{Price Impact}_k = \frac{2D_k(M_{k+5} - M_k)}{M_k} \tag{A4}$$

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

Appendix A.3. News Classification

Below, we explain in a decision tree how we classify news categories used in our analyses.

Figure A.1. News Classification



Appendix A.4. 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 2, we include 37 variables, both RTH and AHT. In Panel B of Figure 2, 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. Market Reaction to AHT News

Do stock returns react to news released after the markets close? If yes, does the reaction depend on the news content? A broad literature shows that news could induce attention-driven demand (Heston and Sinha, 2017; Fedyk, 2025) not only from retail investors, but also from 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[31] 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.[32] 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, 2022).

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. 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.

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

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

Table B.1 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-hours news sentiment and no-news baseline. We define *Good News* (*Bad News*) if the adjusted RavenPack news sentiment scores from 4:00 p.m. to 8:00 p.m. 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) refer to the trading session from 9:30 a.m. to 4:00 p.m. After-hours trading (AHT) refers to the trading session from 4:00 p.m. to 8:00 p.m.

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}	$R_{FF,t+1}^{RTH}$
AHT 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)

Appendix C. Robustness: Random Forest Algorithm

Appendix C.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 C.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 C.2. SHAP Value

SHAP (Shapley Additive exPlanations, (Lundberg and Lee, 2017)) is another popular method to rank the variables (i.e., features) in machine learning algorithms. The method uses the cooperative game theory to derive the Shapley values. The SHAP method 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 C.2 shows the results. It confirms that Cboe EDGX buyer-initiated odd-lot trade has the highest power to explain Robinhood Popularity.

Appendix C.3. XGBoost Feature Importance

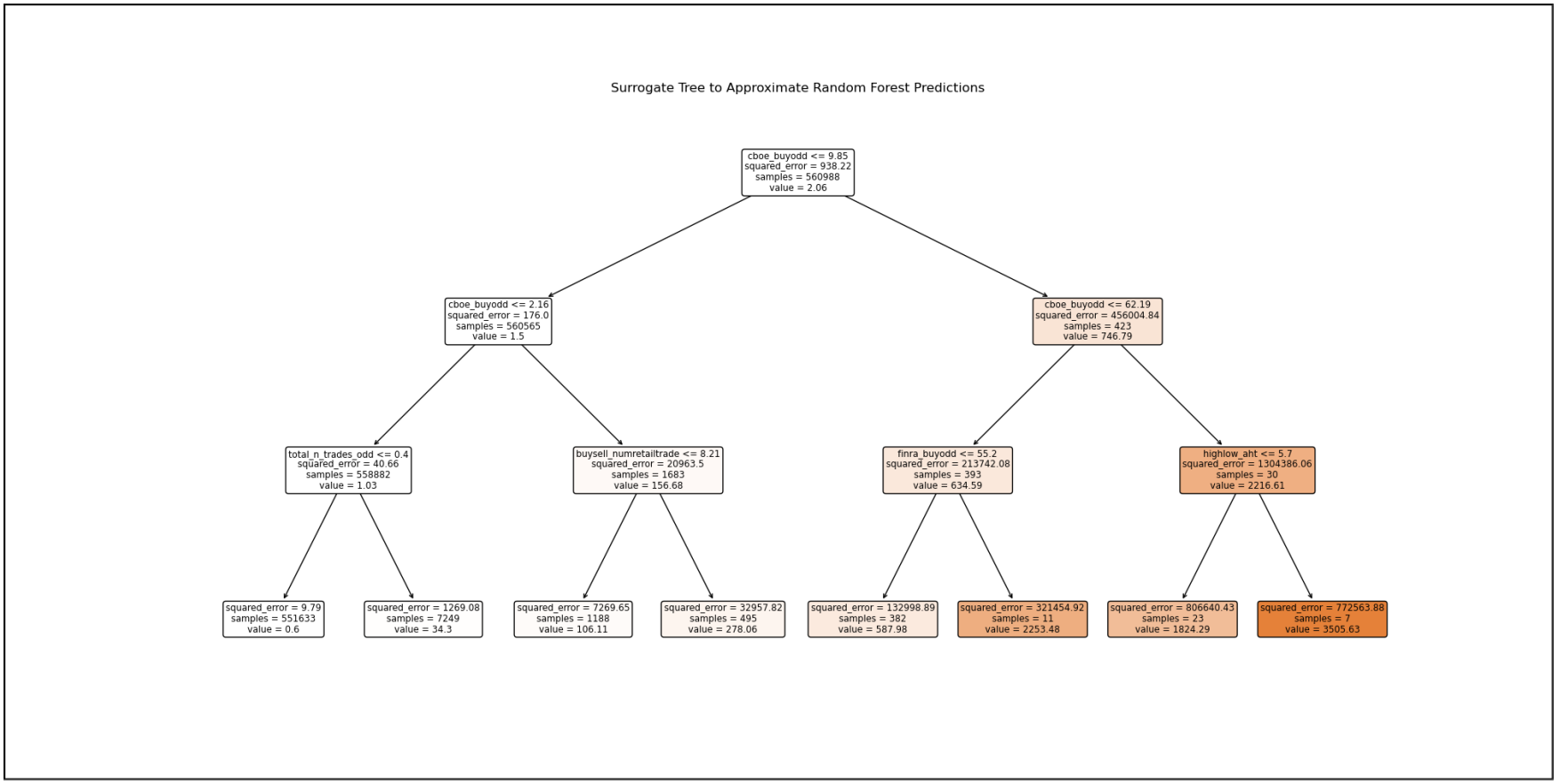
Extreme Gradient Boosting, or XGBoost, is a distributed gradient-boosted decision tree (GBDT) machine learning toolkit. It is one of the top machine learning algorithms for tasks including regression and offers parallel tree boosting. It is often used due to its high predictive accuracy and handling of missing data points. Figure C.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 C.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.

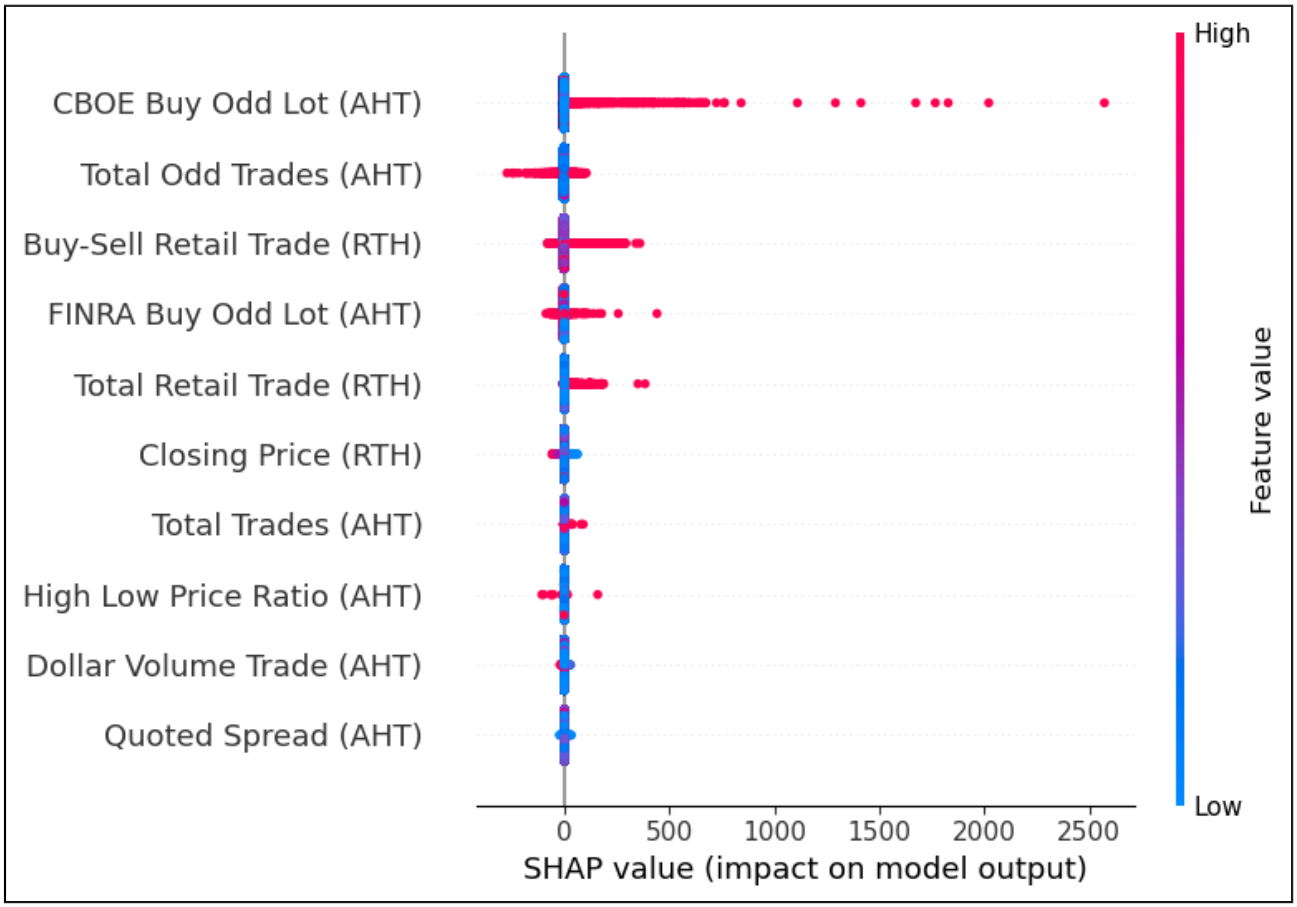
We adopt one of the most common cross-validation techniques, k-fold cross-validation analysis. In K-Fold Cross Validation, the dataset is divided into k folds or subsets, and all of the subsets are trained, with one (k-1) subset set aside for the trained model's evaluation. This approach iterates k times, each time using a distinct subset put aside for testing. Figure C.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 C.1. Surrogate Tree



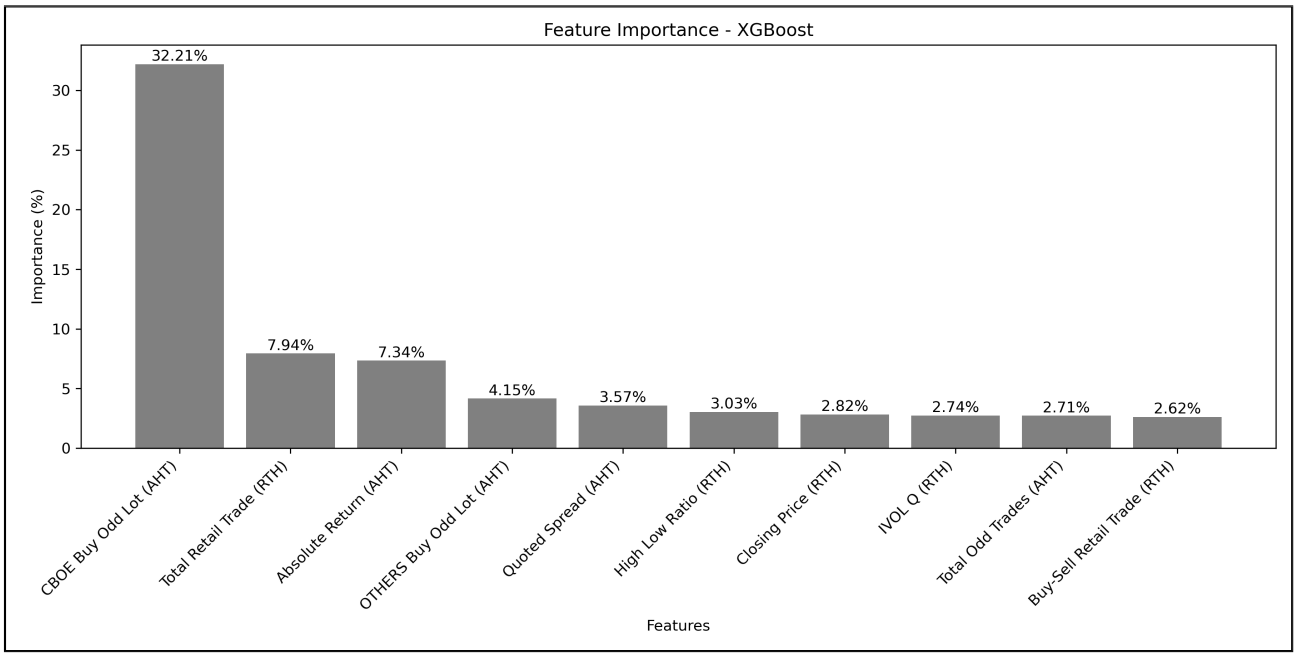
This figure plots the Surrogate Decision Tree model. It is constructed with a three-level tree and a piecewise-constant function with eight leaves. We include 41 observations as in Panel B of Figure 4.

Figure C.2. SHAP Value



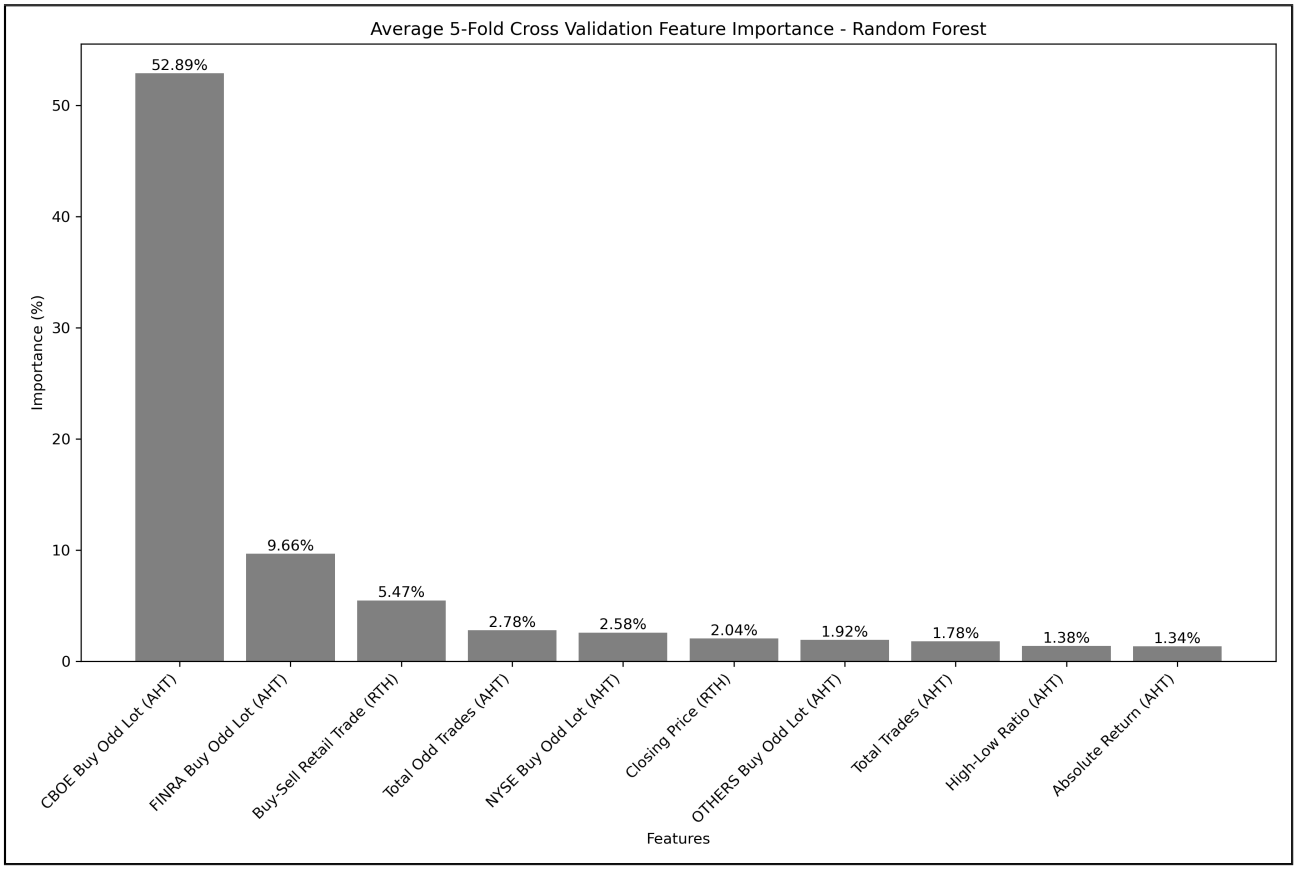
This figure plots the rank of features based on SHAP values (SHapley Additive exPlanations, (Lundberg and Lee, 2017)). We include 41 observations as in Panel B of Figure 4.

Figure C.3. XGBoost Feature Importance



This figure plots the feature importance of Extreme Gradient Boosting, or XGBoost machine learning algorithm. We include 42 observations as in Panel B of Figure 4.

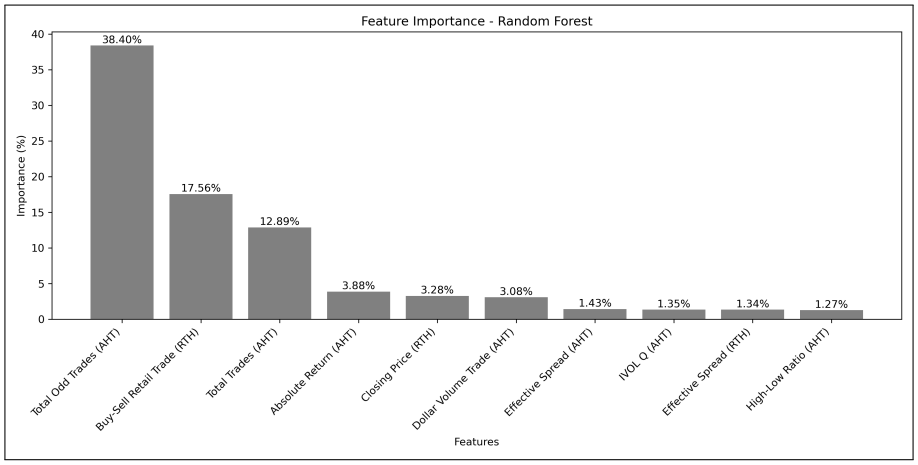
Figure C.4. Feature Importance - Cross-Validation



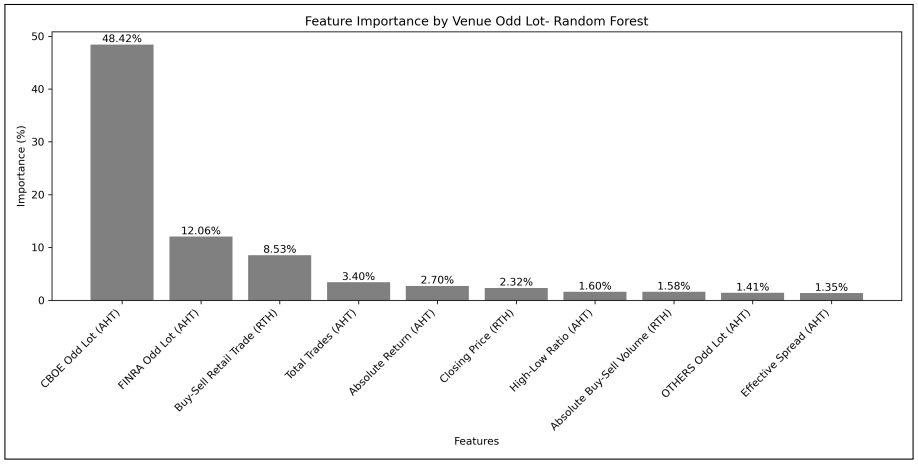
This figure plots the 5-fold average cross-validation feature importance using the Random Forest algorithm. The sample period is from May 3, 2018, to May 27, 2020. We include 42 observations as in Panel B of Figure 4.

Figure C.5. Odd-lot Trades (Without Trade Sign)

(a) Feature Importance

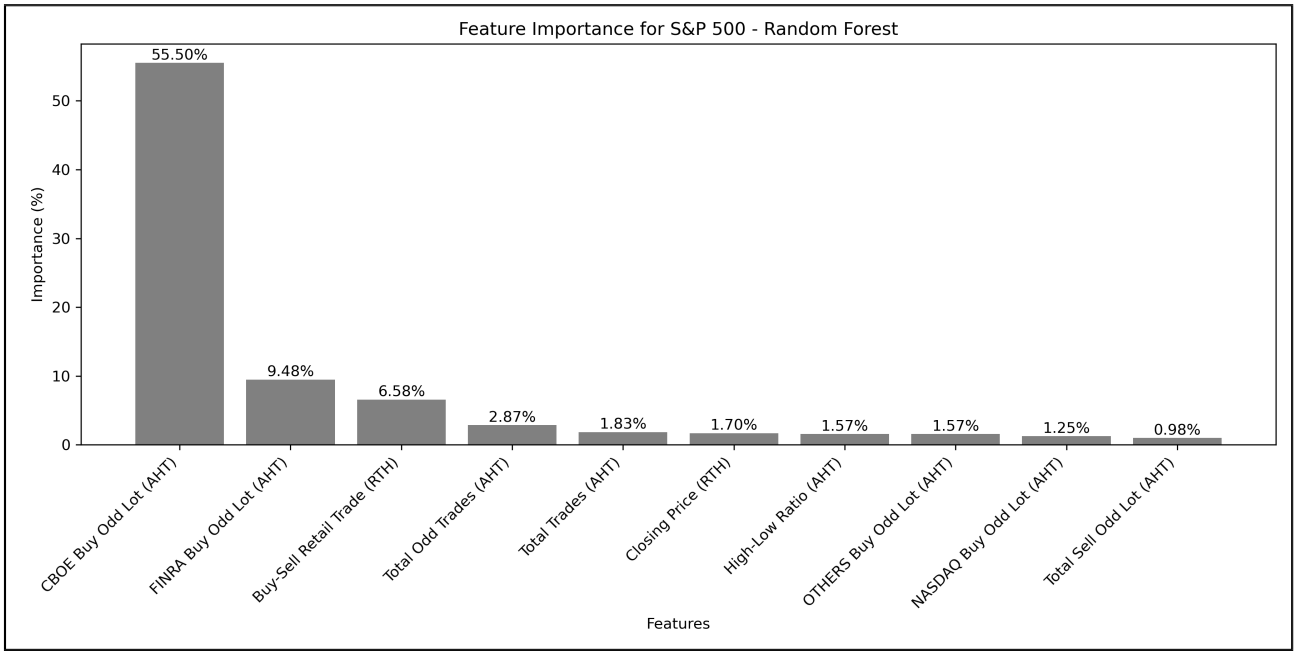


(b) Feature Importance - By Venue



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 4:00 p.m. and 8:00 p.m. AHT odd-lot trades are not signed as buyer or seller-initiated trades. In Panel B, the trading venues include Cboe EDGX, 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.

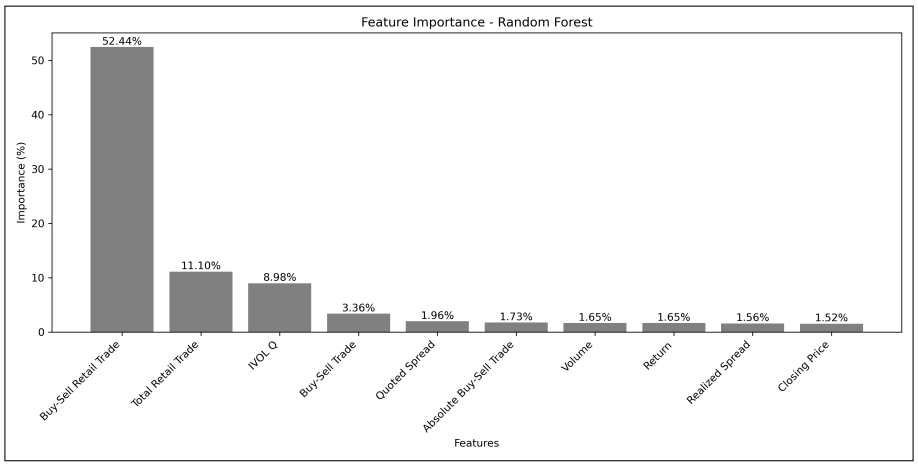
Figure C.6. S&P 500 Stocks



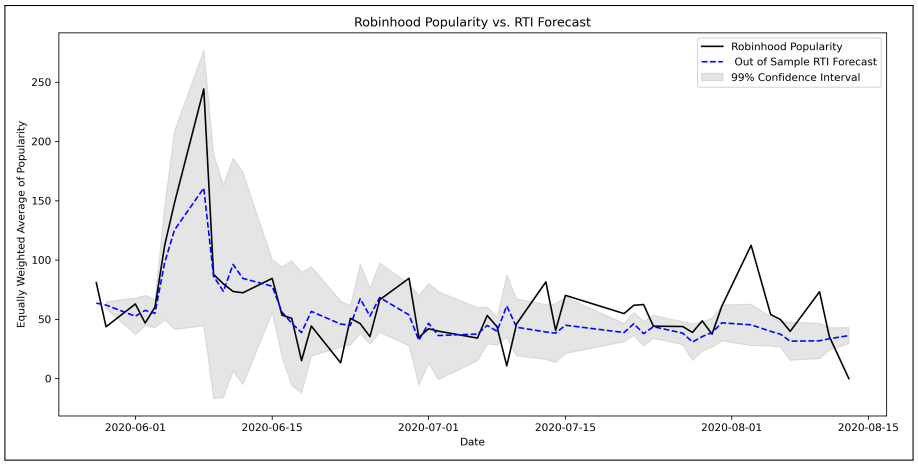
This figure ranks features by their importance according to Random Forest's internal procedure that ranks features based on the total reduction in Gini impurity (a default option that aggregates the importance of each feature across all splits where the feature was used). The target variable is the absolute value of the difference in the number of users holding S&P 500 constituents on Robinhood for each day between 4:00 p.m. and 8:00 p.m. In Panel B, the trading venues include Cboe EDGX, 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 C.7. Regular Trading Hours

(a) Feature Importance



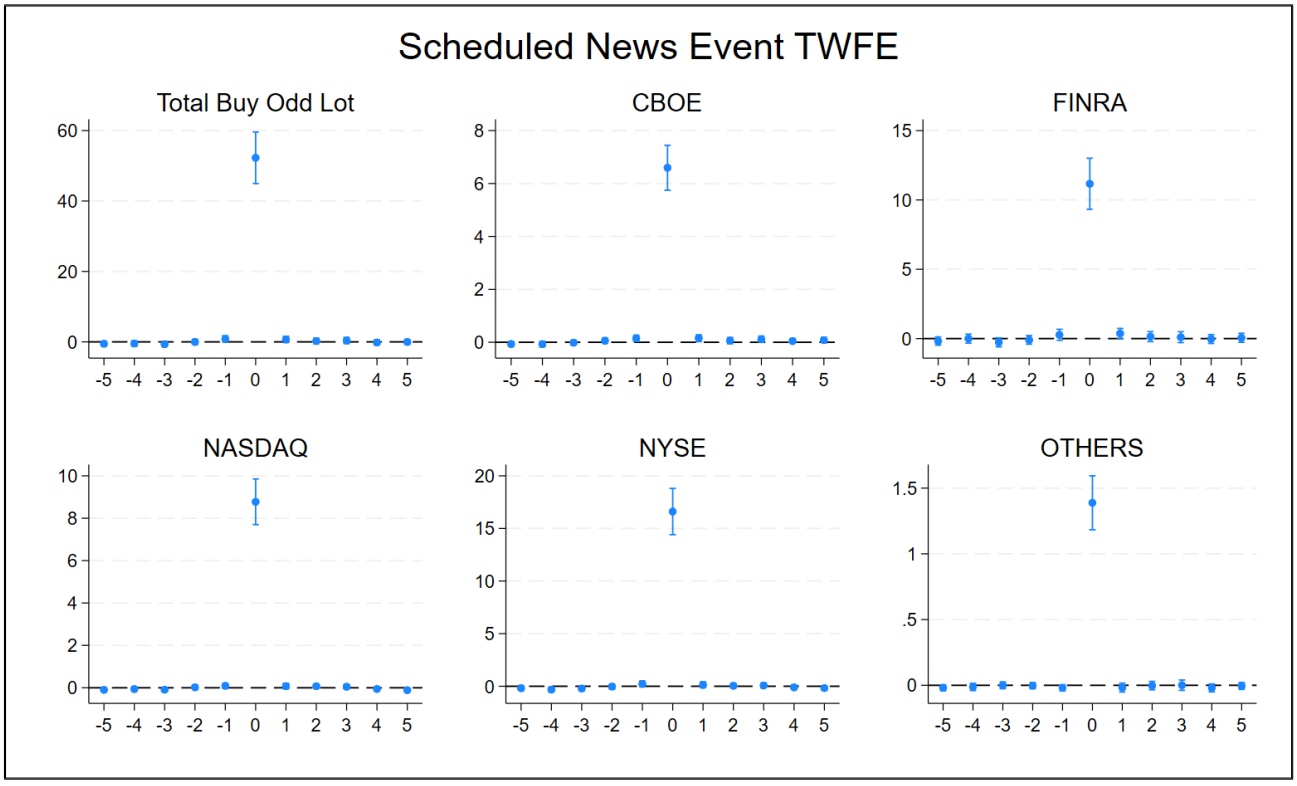
(b) Robinhood Popularity Forecast



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 9:30 a.m. and 4:00 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 9:30 a.m. and 4:00 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.

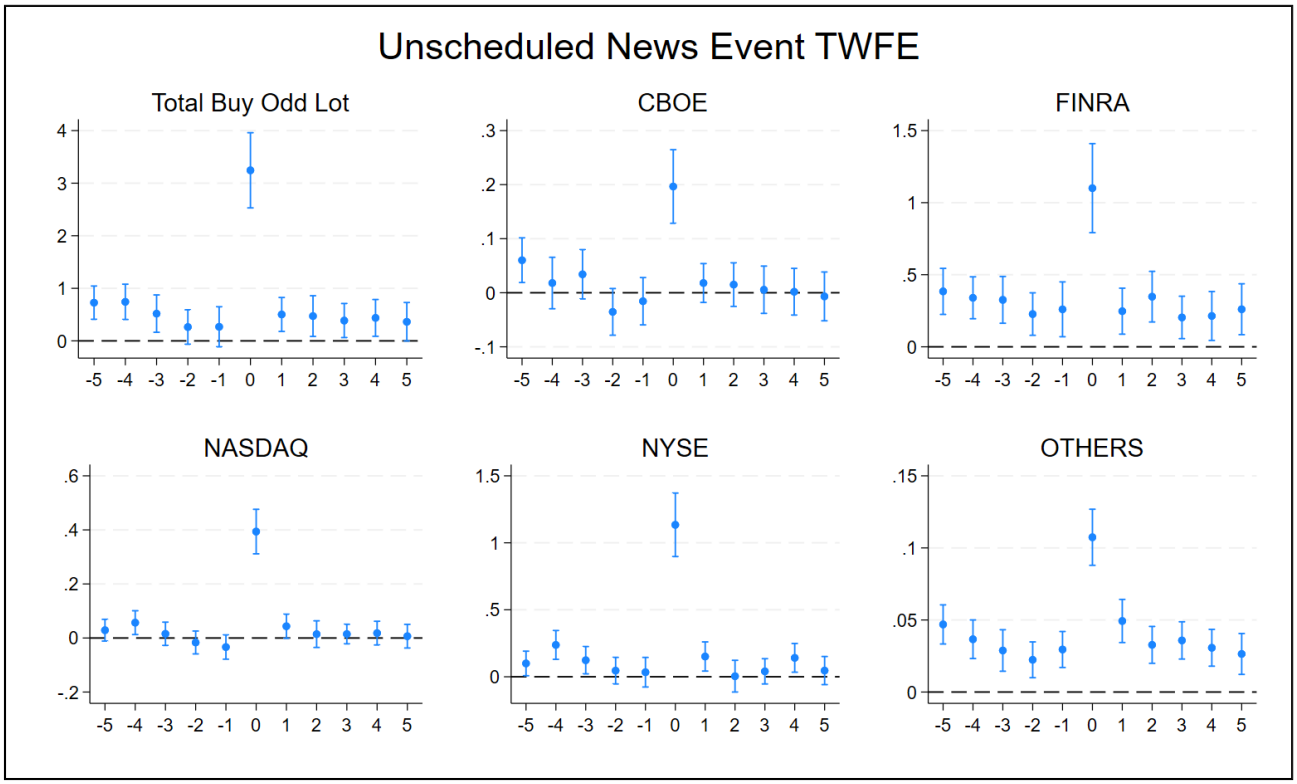
Appendix D. Two-way Fixed Effects Regressions

Figure D.1. Scheduled News



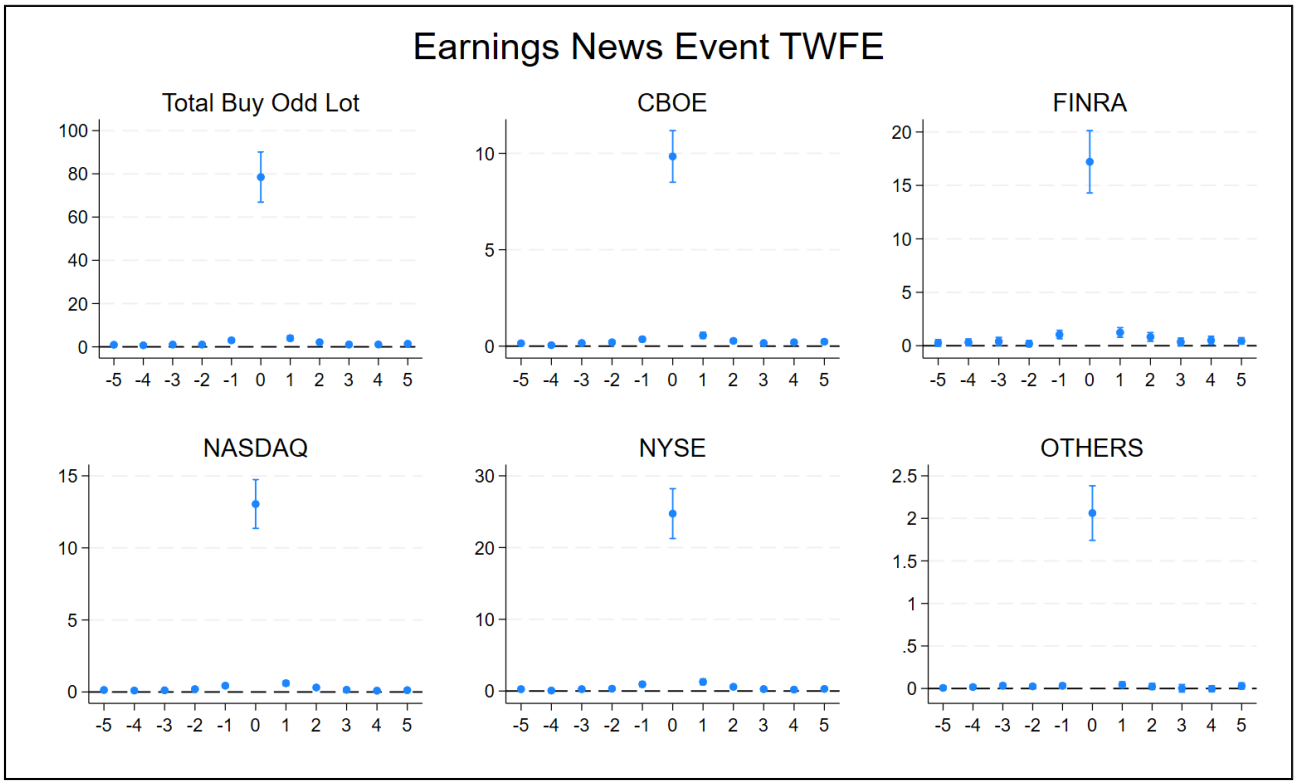
This figure shows the results of the two-way fixed effects model (Equation 6) around scheduled news days. The sample covers from August 1, 2018, to October 31, 2022. The trading venues include the Cboe EDGX, platforms that report to the FINRA alternative display facility (ADF), NASDAQ, NYSE, and other smaller exchanges.

Figure D.2. Unscheduled News



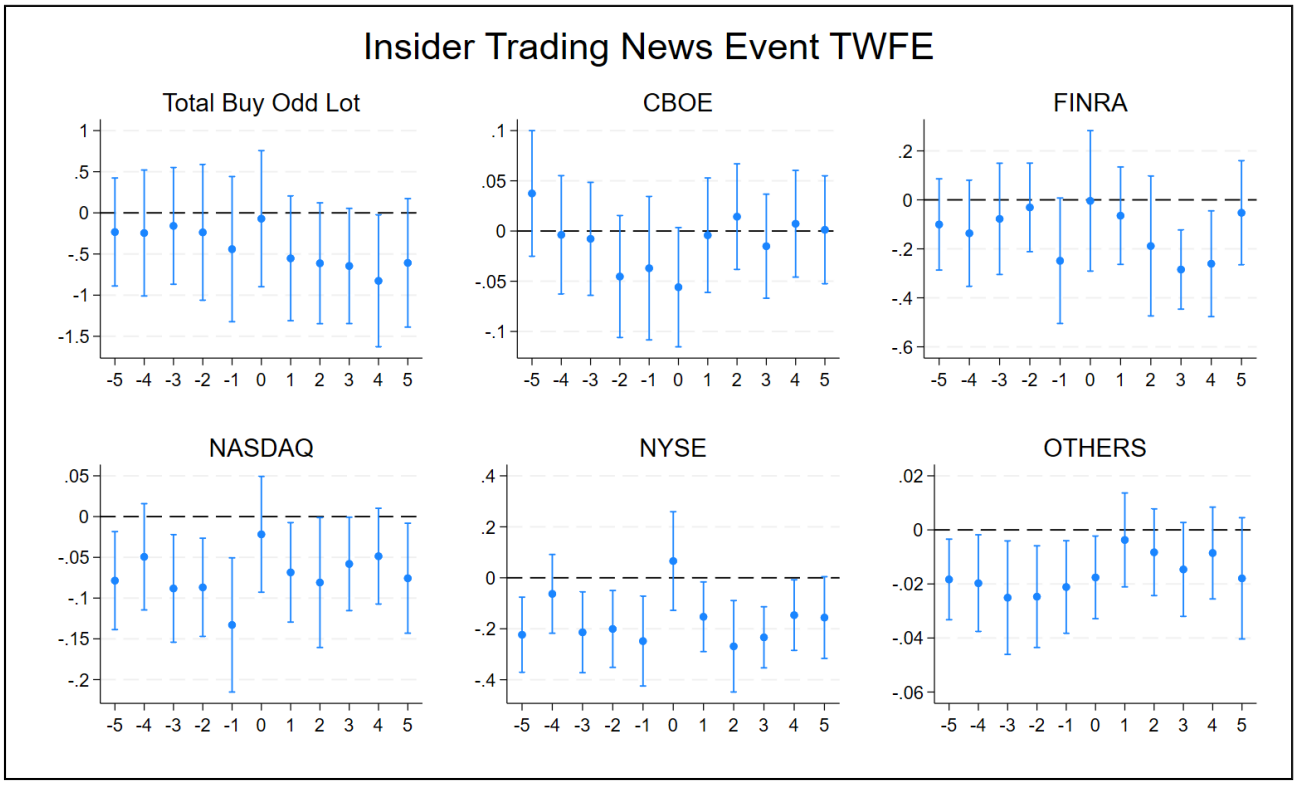
This figure shows the results of the two-way fixed effects model (Equation 6) around unscheduled news days. The sample covers from August 1, 2018, to October 31, 2022. The trading venues include the Cboe EDGX, platforms that report to the FINRA alternative display facility (ADF), NASDAQ, NYSE, and other smaller exchanges.

Figure D.3. Earnings News



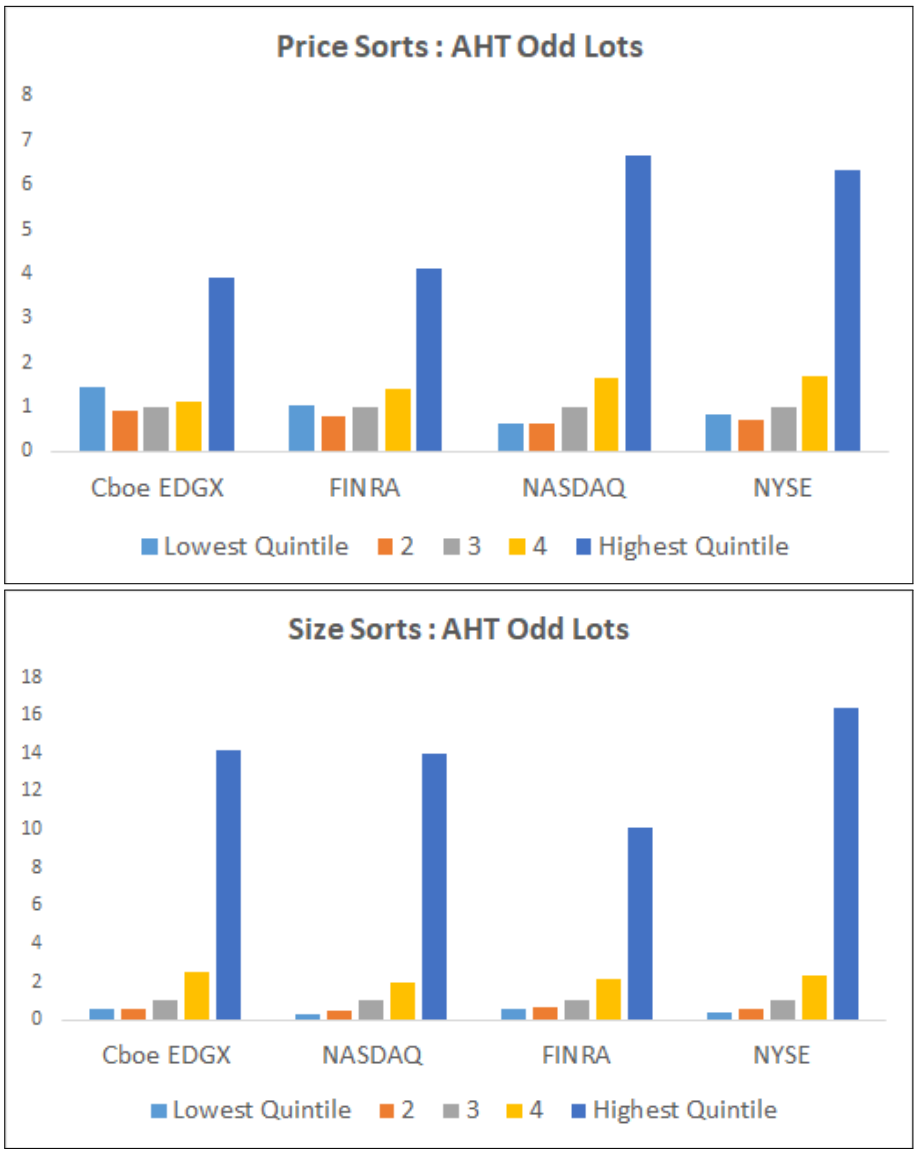
This figure shows the results of the two-way fixed effects model (Equation 6) around earnings news days. The sample covers from August 1, 2018, to October 31, 2022. The trading venues include the Cboe EDGX, platforms that report to the FINRA alternative display facility (ADF), NASDAQ, NYSE, and other smaller exchanges.

Figure D.4. Insider Trading News



This figure shows the results of the two-way fixed effects model (Equation 6) around insider news days. The sample covers from August 1, 2018, to October 31, 2022. The trading venues include the Cboe EDGX, platforms that report to the FINRA alternative display facility (ADF), NASDAQ, NYSE, and other smaller exchanges.

Appendix E. Sorts by Firm Characteristics



This figure shows the average number of AHT odd lot trades on different venues for stocks in the same quantile, sorted daily by firm closing price and firm size (market capitalization). The sample covers from August 1, 2018, to October 31, 2022. The trading venues include the Cboe EDGX, NASDAQ, platforms that report to the FINRA alternative display facility (ADF), and NYSE.

Appendix F. Panel Regressions: Robinhood Period

This section shows the panel regression results only in the Robinhood sample. The sample period is from August 1, 2018, to August 13, 2020. Table F.1 shows the panel regressions where the dependent variable is the next-day return (reversals). Table F.2 shows the panel regressions where the dependent variable is contemporaneous liquidity proxies.

Table F.1 Panel Regressions: Stock Returns

This table reports the results of panel regressions, including stock returns and retail participation for the Robinhood period. The dependent variable $r_{i,t+1}$ is the next-day open-to-close stock i return on day t. $r_{i,t}^{AHT}$ is the after-hours return calculated as the price changes between 4:00 p.m. and 8:00 p.m. The retail trading proxy $RT_{i,t}^{AHT}$ is captured by the Robinhood retail popularity. News days are identified when non-neutral firm-specific news is announced only during after-hours trading (AHT). On no-news days, either no news or neutral news is announced during AHT and RTH. We include time and firm fixed effects in the specification and cluster error at the firm level. The sample period is from August 1, 2018, to August 13, 2020. 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.

	All	All	All	AHT News	AHT News	AHT News	No-News	No-News	No-News
	$r_{i,t+1}$	$r_{i,t+1}$	$r_{i,t+1}$	$r_{i,t+1}$	$r_{i,t+1}$	$r_{i,t+1}$	$r_{i,t+1}$	$r_{i,t+1}$	$r_{i,t+1}$
$r_{i,t}^{AHT}$	-0.022	-0.010	-0.010	0.009	0.019	0.017	-0.028	-0.010	-0.010
	(-1.119)	(-0.528)	(-0.503)	(0.409)	(0.847)	(0.704)	(-1.148)	(-0.441)	(-0.400)
$RT_{i,t}^{AHT}$		-0.008***	-0.009***		-0.014**	-0.014**		0.000	-0.001
		(-2.820)	(-3.015)		(-2.330)	(-2.312)		(0.030)	(-0.055)
$r_{i,t}^{AHT} \times RT_{i,t}^{AHT}$		-0.115***	-0.116***		-0.151**	-0.151**		-0.437**	-0.430**
		(-2.715)	(-2.768)		(-2.057)	(-2.041)		(-2.535)	(-2.476)
Controls	No	No	Yes	No	No	Yes	No	No	Yes
Observations	764,110	701,152	699,101	50,424	46,962	46,962	595,876	549,576	549,576
Adjusted R^2	0.207	0.213	0.213	0.142	0.148	0.148	0.217	0.224	0.224

Table F.2 Panel Regressions: Liquidity

This table reports the results of the panel regressions, including liquidity measures and retail participation for the Robinhood period. The dependent variable $y_{i,t}$ is a liquidity measure of the stock i on day t. The retail trading proxy $RT_{i,t}^{AHT}$ is captured by the Robinhood retail popularity. The variable $News_{i,t}^{AHT}$ is a dummy variable, equal to 1 if non-neutral firm-specific news is announced only during after-hours trading (AHT), and 0 if no news or neutral news is announced during AHT and RTH. On no-news days, either no news or neutral news is announced during AHT and RTH.. We control for time and firm Fixed effects. The sample period is from August 1, 2018, to August 13, 2020. 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.

Panel A. News	Quoted Spread$_{i,t}$	Effective Spread$_{i,t}$	Realized Spread$_{i,t}$	Price Impact$_{i,t}$
$RT_{i,t}^{AHT}$	-0.655***	-0.116***	-0.144***	0.015**
	(-3.028)	(-3.169)	(-3.362)	(2.524)
$News_{i,t}^{AHT}$	-12.399***	19.650***	12.034***	5.467***
	(-5.124)	(14.558)	(8.502)	(7.085)
$RT_{i,t}^{AHT}$*$News_{i,t}^{AHT}$	0.520**	0.099**	0.114**	-0.008
	(2.259)	(2.366)	(2.273)	(-1.111)
Obs.	540,355	528,445	527,458	527,458
Adj. R^2	0.420	0.203	0.137	0.005
Panel B. Earnings News				
$RT_{i,t}^{AHT}$	-0.617***	-0.115***	-0.144***	0.012***
	(-3.737)	(-3.893)	(-4.122)	(2.698)
$News_{i,t}^{AHT}$	-20.113**	128.664***	79.391***	34.439***
	(-2.267)	(24.249)	(15.139)	(13.821)
$RT_{i,t}^{AHT}$*$News_{i,t}^{AHT}$	0.570***	0.083**	0.120***	-0.014***
	(3.413)	(2.021)	(2.915)	(-2.999)
Obs.	540,355	528,445	527,458	527,458
Adj. R^2	0.420	0.205	0.138	0.005

Appendix G. Panel Regressions: Odd Lot Proxy

This section shows the panel regression results using the number of odd-lot trades on the Cboe EDGX as a proxy for Robinhood retail popularity between May 3, 2018, and October 31, 2022. Table G.1 shows the panel regressions where the dependent variable is the next-day return (reversals). Table G.2 shows the panel regressions where the dependent variable is contemporaneous liquidity proxies.

Table G.1 Panel Regressions: Stock Returns

This table reports the results of panel regressions, including stock returns and retail participation. The dependent variable $r_{i,t+1}$ is the next-day open-to-close stock i return on day t. $r_{i,t}^{AHT}$ is the after-hours return calculated as the price changes between 4:00 p.m. and 8:00 p.m. The retail trading proxy $RT_{i,t}^{AHT}$ is captured by the number of odd-lot trades on Cboe EDGX between August 1, 2018, and October 31, 2022. News days are identified when non-neutral firm-specific news is announced only during after-hours trading (AHT). On no-news days, either no news or neutral news is announced during AHT and RTH. We include time and firm fixed effects in the specification and cluster error at the firm level. 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.

	All	All	All	AHT News	AHT News	AHT News	No-News	No-News	No-News
	$r_{i,t+1}$	$r_{i,t+1}$	$r_{i,t+1}$	$r_{i,t+1}$	$r_{i,t+1}$	$r_{i,t+1}$	$r_{i,t+1}$	$r_{i,t+1}$	$r_{i,t+1}$
$r_{i,t}^{AHT}$	-0.015	-0.013	-0.013	-0.005	0.004	0.001	-0.017	-0.014	-0.014
	(-1.359)	(-1.163)	(-1.144)	(-0.341)	(0.284)	(0.059)	(-1.277)	(-1.084)	(-1.012)
$RT_{i,t}^{AHT}$		-0.002**	-0.002***		-0.002**	-0.002***		-0.004*	-0.004*
		(-2.534)	(-2.645)		(-2.545)	(-2.635)		(-1.708)	(-1.777)
$r_{i,t}^{AHT} \times RT_{i,t}^{AHT}$		-0.005***	-0.005***		-0.027**	-0.027**		-0.099**	-0.099**
		(-3.734)	(-3.592)		(-2.210)	(-2.165)		(-1.977)	(-1.990)
Controls	No	No	Yes	No	No	Yes	No	No	Yes
Observations	1,589,336	1,585,481	1,571,336	134,814	134,632	134,453	1,213,341	1,210,023	1,208,923
Adjusted R^2	0.221	0.221	0.220	0.172	0.173	0.173	0.232	0.232	0.232

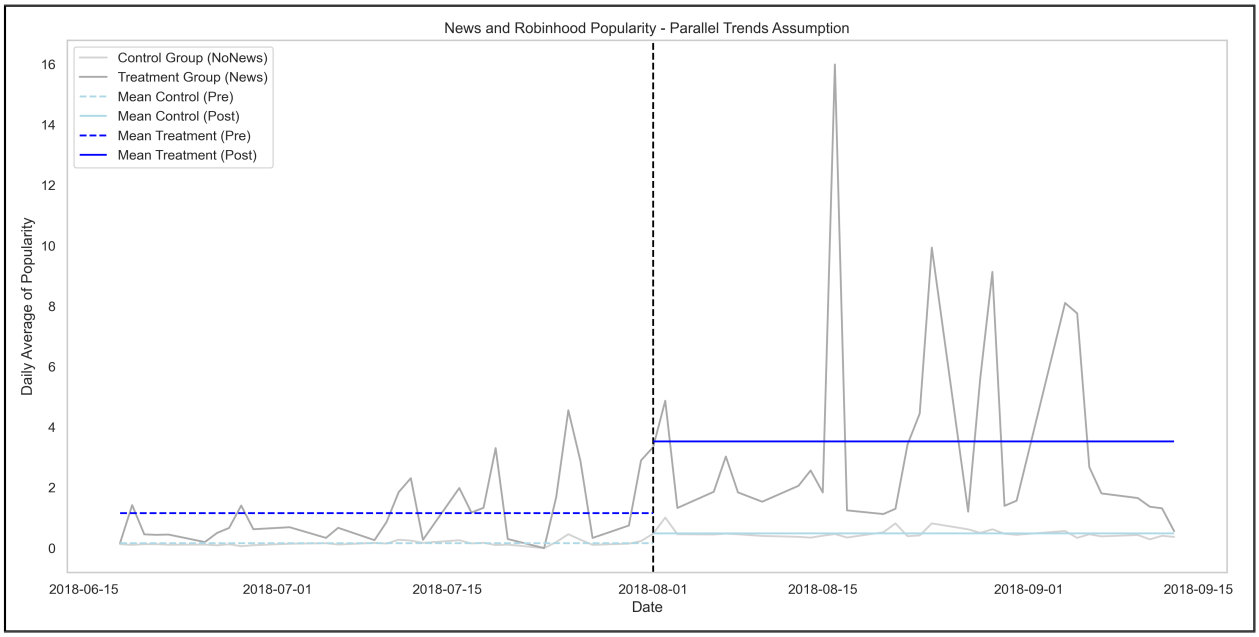
Table G.2 Panel Regressions: Liquidity

This table reports the results of the panel regressions, including liquidity measures and retail participation. The dependent variable $y_{i,t}$ is a liquidity measure of the stock i on day t. The retail trading proxy $RT_{i,t}^{AHT}$ is captured by the number of odd-lot trades on Cboe EDGX between August 1, 2018, and October 31, 2022. The variable $News_{i,t}^{AHT}$ is a dummy variable, equal to 1 if non-neutral firm-specific news is announced only during after-hours trading (AHT), and 0 if no news or neutral news is announced during AHT and RTH. We control for time and firm Fixed effects. The sample period is from August 1, 2018, to October 31, 2022. 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.

Panel A. News	Quoted Spread$_{i,t}$	Effective Spread$_{i,t}$	Realized spread$_{i,t}$	Price impact$_{i,t}$
$RT_{i,t}^{AHT}$	-0.349***	-0.062***	-0.077***	0.007***
	(-5.876)	(-6.195)	(-6.105)	(3.088)
$News_{i,t}^{AHT}$	-40.645***	6.302***	1.142	4.589***
	(-16.646)	(6.688)	(1.225)	(9.212)
$RT_{i,t}^{AHT}$*$News_{i,t}^{AHT}$	0.303***	0.057***	0.065***	-0.003
	(5.191)	(5.396)	(5.015)	(-1.087)
Obs.	1,237,280	1,225,580	1,224,594	1,224,594
Adj. R^2	0.510	0.204	0.136	0.007
Panel B. Earnings News				
$RT_{i,t}^{AHT}$	-0.220***	-0.043***	-0.055***	0.005***
	(-5.027)	(-5.779)	(-5.877)	(3.457)
$News_{i,t}^{AHT}$	-55.281***	112.943***	70.158***	32.758***
	(-8.828)	(29.499)	(19.385)	(17.422)
$RT_{i,t}^{AHT}$*$News_{i,t}^{AHT}$	0.201***	0.012	0.030**	-0.008***
	(4.624)	(1.021)	(2.489)	(-4.370)
Obs.	1,237,280	1,225,580	1,224,594	1,224,594
Adj. R^2	0.509	0.205	0.136	0.007

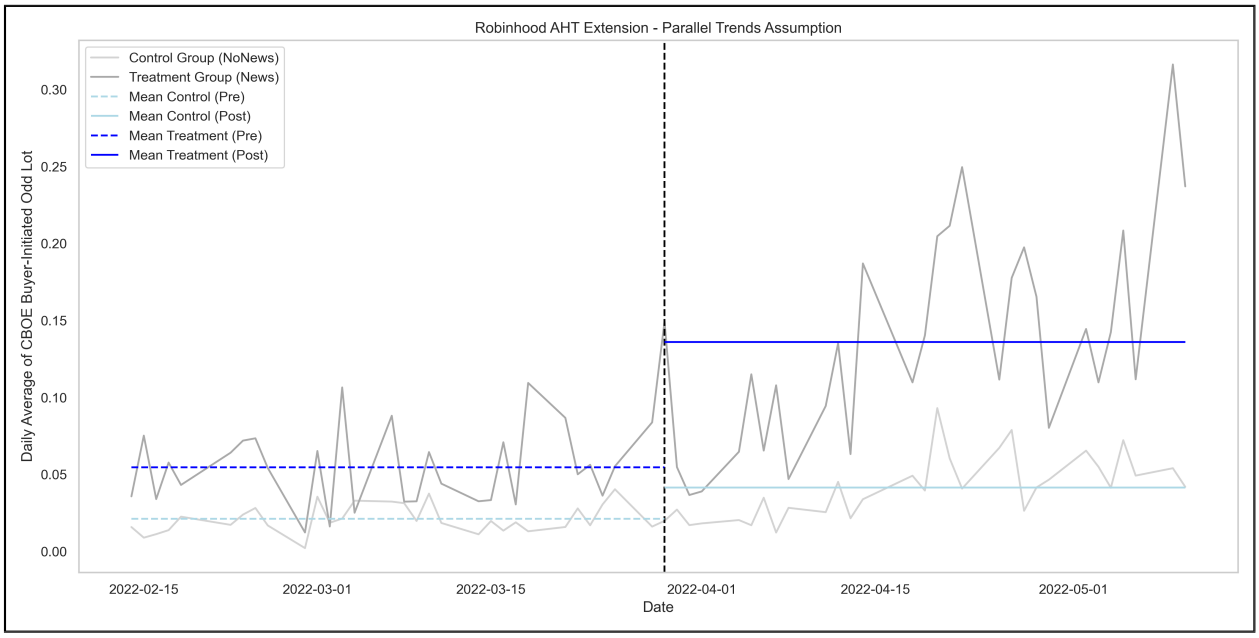
Appendix H. DiD Analysis: Parallel Trends

Figure H.1. DiD Analysis: News and Robinhood Popularity



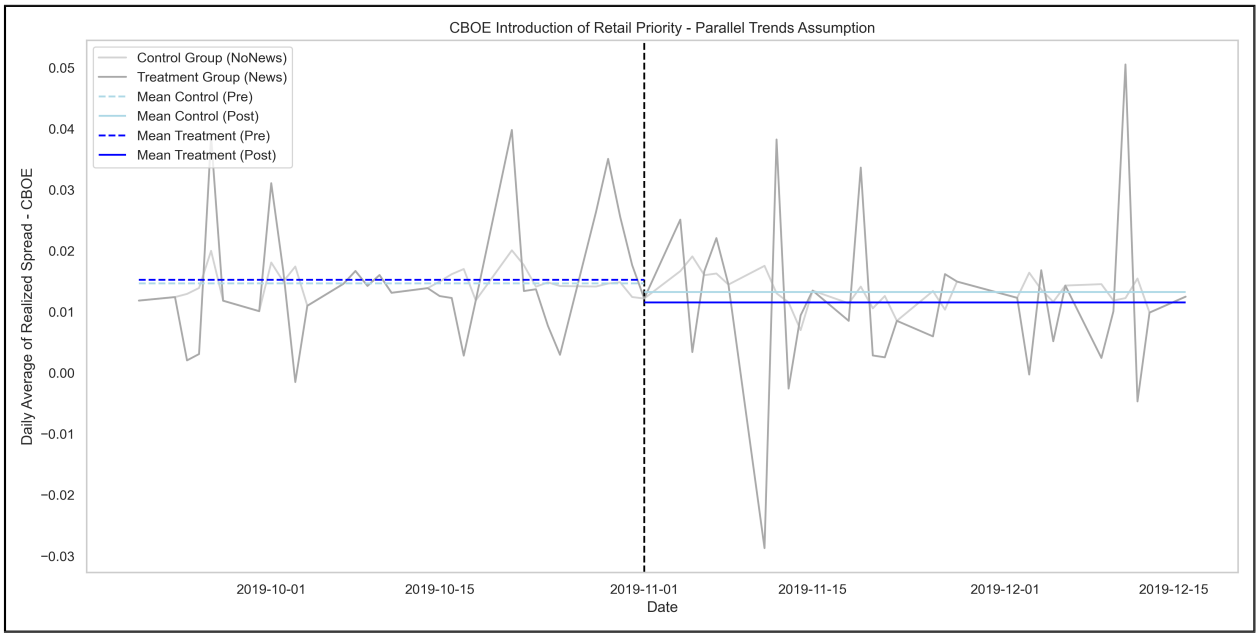
This figure shows the daily average of the AHT popularity of the stock i on day t on the Robinhood platform, $Popularity_{i,t}^{AHT}$ on the $News_{i,t}^{AHT}$ days (treatment) when there is firm-specific news announced during AHT, and zero (control) when no news is announced. *No News* refers to no news announcements or an accumulation of neutral news in AHT and RTH. The horizontal dashed (solid) lines show that pre-event (post-event) average values for the treatment (dark blue) and control (light blue) groups. The vertical line indicates August 1, 2018, when the Robinhood platform opened AHT to all customers.

Figure H.2. DiD Analysis: Robinhood AHT Extension



This figure shows the daily average of the total buyer-initiated odd-lot trades from 6:00 p.m. to 8:00 p.m.(normalized by the trades from 4:00 p.m. to 6:00 p.m.) of stock i on day t on the Cboe exchange on the $News_{i,t}^{AHT}$ days (treatment) when there is firm-specific news announced during AHT, and zero (control) when no news is announced. *No News* refers to no news announcements or an accumulation of neutral news in AHT and RTH. The horizontal dashed (solid) lines show that pre-event (post-event) average values for the treatment (dark blue) and control (light blue) groups. The vertical line indicates March 29, 2022, when the Robinhood platform extended AHT until 8:00 p.m.

Figure H.3. DiD Analysis: Cboe EDGX Introduction of Retail Priority



This figure shows the daily average of the realized spread around the buyer-initiated (Panel A) and seller-initiated (Panel B) odd-lot trades from 4:00 p.m. to 8:00 p.m. of stock i on day t on the Cboe exchange on the $E_{i,t}^{AHT}$ days (treatment) when there is firm-specific earnings news announced during AHT, and zero (control) when no news is announced. *No News* refers to no news announcements or an accumulation of neutral news in AHT and RTH. The horizontal dashed (solid) lines show that pre-event (post-event) average values for the treatment (dark blue) and control (light blue) groups. The vertical line indicates November 1, 2019, when Cboe Exchange introduced retail priority on the EDGX platform.

Appendix I. 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 4:00:00 p.m. are excluded to avoid the immediate effects of extended trading hours and the closing auction during regular trading hours. This exclusion ensures that our event window, defined as 5 minutes before to 5 minutes 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 [I.1] presents the final sample of 56 events, along with the event window returns and cumulative adjusted RavenPack news sentiment scores for each event.

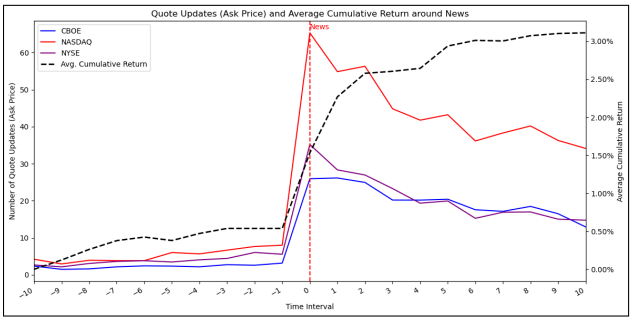
Table I.1 Earnings News Events

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

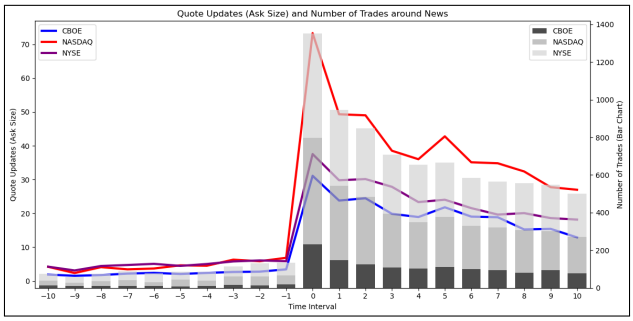
Date	Time	Firm	Sentiment Score	Return
2019-01-29	16:30:00	Apple Inc.	0.36	3.04%
2019-07-30	16:30:00	Apple Inc.	0.12	3.07%
2019-10-30	16:30:00	Apple Inc.	0.42	1.93%
2020-01-28	16:30:00	Apple Inc.	1.28	2.36%
2020-04-30	16:30:00	Apple Inc.	2.04	2.20%
2020-07-30	16:30:00	Apple Inc.	1.06	4.14%
2021-04-28	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 I.1. Positive Earnings News

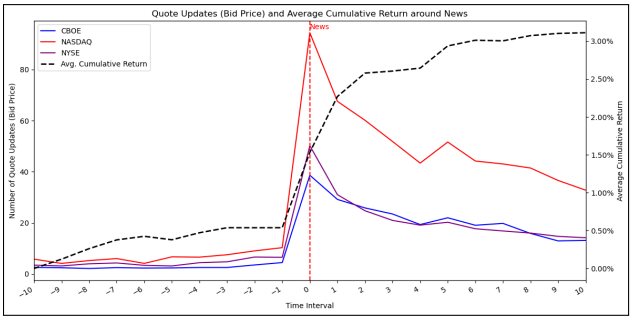
(a) Ask Price



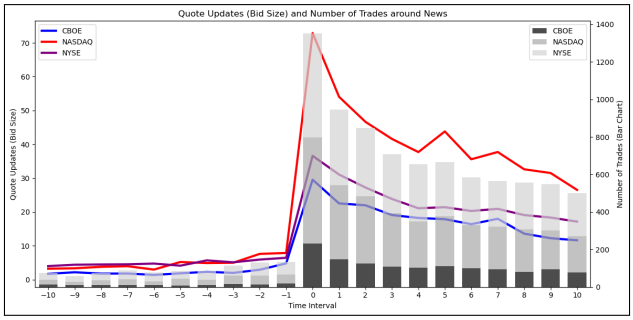
(b) Ask Size



(c) Bid Price



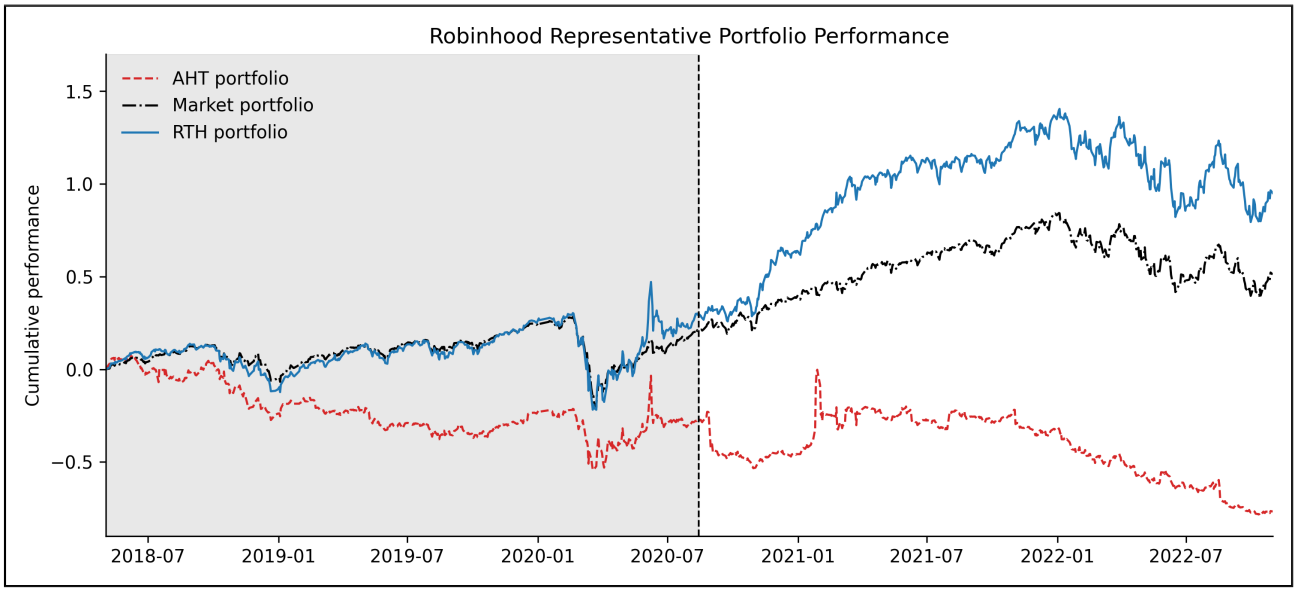
(d) Bid Price



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.

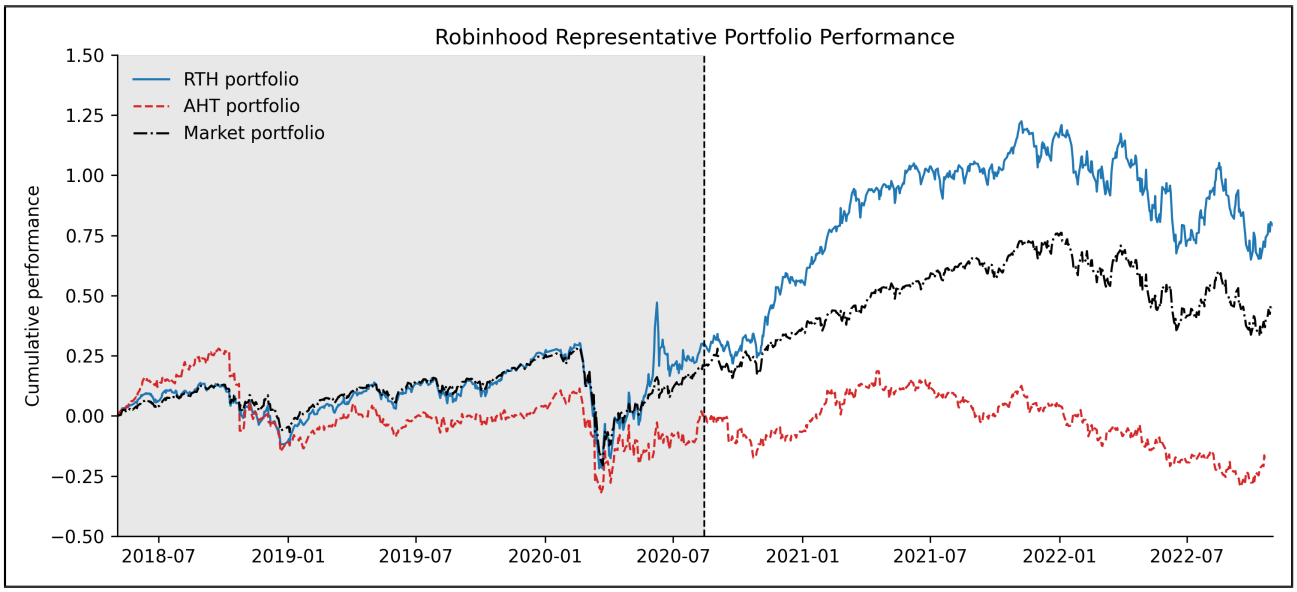
Appendix J. Portfolio Analysis

Figure J.1. AHT retail portfolio



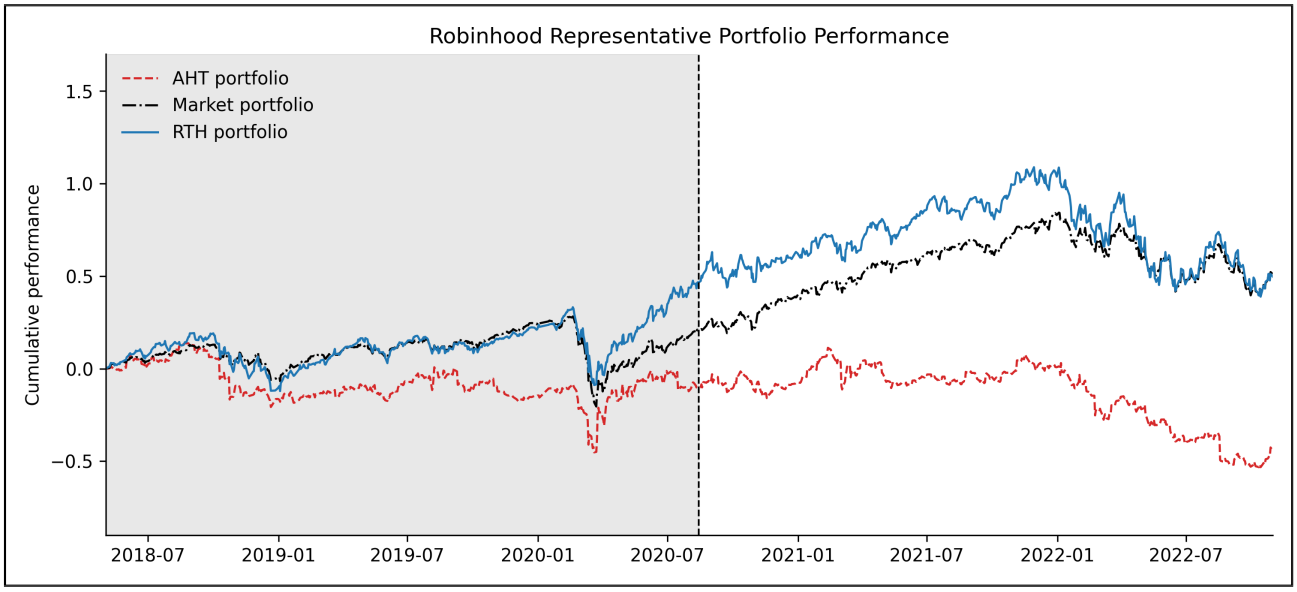
This figure shows the cumulative return performance of the benchmark Robinhood representative portfolio (ARH^{RTH}), the market portfolio (S&P 1500) and the AHT retail portfolio (ARH^{AHT}), both for the Robinhood sample from May 3, 2018, to August 13, 2020 (vertical line) and the extended predicted sample until October 31, 2022.

Figure J.2. News-driven AHT retail portfolio (user holdings)



This figure shows the cumulative return performance of the benchmark Robinhood representative portfolio (ARH^{RTH}), the market portfolio (S&P 1500) and the news-driven AHT retail portfolio (ARH^{AHT}) based on Robinhood user holdings, both for the Robinhood sample from May 3, 2018, to August 13, 2020 (vertical line) and the extended predicted sample until October 31, 2022.

Figure J.3. News-driven AHT retail portfolio (share method)



This figure shows the cumulative return performance of the benchmark Robinhood representative portfolio (share method) (ARH^{RTH}), the market portfolio (S&P 1500) and the news-driven AHT retail portfolio (ARH^{AHT}) based on share method, that is, each investors representing one share investment in each stock, both for the Robinhood sample from May 3, 2018, to August 13, 2020 (vertical line) and the extended predicted sample until October 31, 2022.

Table J.1 Portfolio Performance: Alternative AHT Retail Portfolios

The table reports regression results for alternative AHT retail portfolios. Panel A reports results without news restriction, and Panel B reports results for the User Holding specification. We report CAPM and 6-factor models for the Robinhood period and the full sample. Factor data are from Kenneth R. French's data library. Newey–West t-statistics (in parentheses) are reported using optimal lag selection.

Panel A. AHT Retail Portfolio – Excluding News Restriction

	Robinhood Period			Full Sample	
	CAPM	6-Factor Model		CAPM	6-Factor Model
alpha	-0.076	-0.047	alpha	-0.141**	-0.149**
	(-1.116)	(-0.800)		(-1.986)	(-2.299)
XMKT	1.227***	1.065***	XMKT	1.197***	1.161***
	(16.144)	(16.894)		(19.072)	(24.045)
SMB		0.353**	SMB		0.704***
		(2.182)			(4.562)
HML		0.194	HML		-0.075
		(0.774)			(-0.356)
RMW		0.276	RMW		0.124
		(0.613)			(0.630)
CMA		-0.631	CMA		0.654
		(-1.376)			(1.190)
MOM		-0.477	MOM		-0.311**
		(-1.378)			(-2.404)
R-Squared	49.27%	58.75%	R-Squared	31.87%	37.44%
Observations	546	546	Observations	1,098	1,098

Panel B. News-driven AHT Retail Portfolio – User Holdings

	Robinhood Period			Full Sample	
	CAPM	6-Factor Model		CAPM	6-Factor Model
alpha	-0.018	-0.012	alpha	-0.041	-0.040
	(-0.310)	(-0.192)		(-1.175)	(-1.157)
XMKT	0.915***	0.833***	XMKT	0.912***	0.872***
	(8.427)	(11.802)		(13.175)	(13.973)
SMB		0.448***	SMB		0.459***
		(3.149)			(6.286)
HML		-0.063	HML		0.123
		(-0.270)			(1.081)
RMW		0.290	RMW		0.122
		(1.404)			(1.409)
CMA		-0.530*	CMA		0.042
		(-1.439)			(0.232)
MOM		-0.220	MOM		-0.067
		(-1.370)			(-1.213)
R-Squared	42.14%	46.93%	R-Squared	45.91%	50.26%
Observations	546	546	Observations	1,097	1,097