Democratizing or Demoralizing: The Impact of Robinhood's Order Types on Retail Trading Costs*

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Abstract

Order collaring, which automatically converts default market orders into limit orders with a 5% spread over prior prices, has been used at Robinhood to protect retail investors from trading at unfavorable prices. However, in this paper, we provide empirical evidence that this policy actually harms retail traders by increasing their trading costs. Through quasi-experiments involving Robinhood's trading hours, their extension, the discontinuity around the 5% spread, and the asymmetric implementation of order collaring on retail buy and sell orders, we find that retail traders on Robinhood face higher spreads. Specifically, during regular trading hours, their collared orders execute at an additional spread of 3.6 basis points, and in extended hours, a significant number of their orders execute at a 5% spread over previous trade prices. Furthermore, our analysis of the GameStop short-squeeze episode reveals that the order collaring policy is associated with extreme price movements in stocks.

Keywords: Retail Investors, Order Collaring, Order Anticipation, Volatility

JEL Classification: G12, G14.

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1. Introduction

Retail trading behavior has long been a focus for both academics and regulators. Extensive literature documents that individual traders often exhibit systematic biases (Barber and Odean, 2013). However, the retail trading landscape changed dramatically when Robinhood introduced zero-commission trading in 2013, a move quickly adopted by many brokers amid fierce competition. This shift made stock market participation more affordable for individual investors and significantly increased the number of active retail traders. The trend was further amplified by the "work-from-home" movement during the COVID-19 pandemic, firmly establishing retail traders as a vital part of the U.S. equity markets. Rosenblatt Securities estimates that the market share of retail traders surged to 47% in January 2021 during the peak of the "meme-stock" frenzy. Given their growing prominence and evidence that aggregate retail order imbalances can predict future returns (Boehmer et al., 2021), NASDAQ has begun selling data tracking retail trading activity, which now accounts for over $30 billion in daily trading volume.[1]

As a front-runner driving the shift to zero-commission trading, Robinhood, with its easy-to-use and gamified mobile app, has scored the highest number of retail traders on its platform. In 2022, Robinhood reported 22.9 million funded customer accounts with $71 billion in assets under custody.[2] Given its growing market share, it is important to understand how Robinhood's order handling policies affect its users and market-wide trading costs.

Upon opening the main trading screen on the Robinhood App, an investor faces a particular set of default order options. The investor must designate a trade quantity in dollar or share units. They can then submit their trade on the chosen stock by simply 'swiping up' on the screen. Robinhood automatically converts most default orders into limit orders with a limit price set at 5% above (below) the last traded price for buy (sell) orders. This practice is called order collaring. Robinhood states that the rationale for order collaring policy is to protect its customers from executing at unfavorable prices.[3] For example, if a customer wants to buy one share of a security with a last trade price of $100 via a default order, Robinhood will convert this default order into a limit buy order with a maximum price of $105. If the best available ask is greater than $105, then

[1] https://data.nasdaq.com/databases/RTAT/data

[2] https://investors.robinhood.com/static-files/160af6e8-4d3a-45c3-9f38-d8d99f23d9c7

[3] https://web.archive.org/web/20230123214456/https://robinhood.com/us/en/support/articles/market-order/

this order will not execute, but will potentially be the best bid price at $105. If the best available ask is less than or equal to $105, this order will execute at the best available ask price.

Interestingly, during regular market hours, Robinhood only collars share-based buy orders; if a retail customer wants to sell an existing stock from their portfolio, no collaring applies to that sell order. This strategic choice to collar only buy orders potentially contradicts the "protection motive" mentioned earlier. Thus, an important motivation for order collaring appears to be Robinhood's risk management strategy. Consider this example: if a retail customer has only $100 in their account, their market order to buy a security with a last transaction price of $100 could be risky for Robinhood, as the market order might execute at several cents above $100, leaving the customer's account with a deficit.

Additionally, there may be a revenue generation motive. By encouraging customers to use this order type during extended trading hours, Robinhood increases the likelihood of order execution even in a low-liquidity market. This results in higher trading volumes and, consequently, greater payment for order flow (PFOF) revenue from wholesalers.

One potential harm to retail investors arises from order anticipation. Since retail trading constitutes a substantial share of total market activity, Robinhood's order collaring policy influences how market makers set their quotes during regular trading hours. Given Robinhood's publicly known order collaring policy, strategic traders–particularly wholesaler-linked market makers on public exchanges–are likely to adjust their bid-ask quotes to exploit the higher willingness-to-pay embedded in Robinhood's order types. The high-frequency market-making model proposed by Ait-Sahalia and Sağlam (2024) demonstrates a similar predatory quoting strategy when market makers have signals about low-frequency traders' willingness-to-pay. As a result, the order collaring policy could lead to wider quoted spreads, especially during after-hours trading when execution quality disclosure requirements are less stringent.[4] Since Robinhood investors are typically inexperienced, they may unknowingly use order types subject to collaring more frequently. Thus, our main research question is whether retail traders at Robinhood are subject to higher spreads because of this order collaring policy.

[4]Rule 605 requires that trading centers measure execution quality versus NBBO at the time of order execution. Note, "the Rule applies only to market orders or limit orders that are received by a market center during regular trading hours and, if executed, executed during such time." Full text of Rule 605 can be found at https://www.sec.gov/rules/2001/03/disclosure-order-execution-and-routing-practices

To examine this question empirically, we employ three identification strategies. First, we exploit Robinhood's asymmetric order collaring policy during regular market hours, when share-based buy orders face a 5% collar while sell orders do not. Using stocks with low retail activity as a control group, we find that buy orders incur an additional cost of 3.6 basis points when compared to sell orders in the same set of stocks. Consistently, when Robinhood restricts buying on a set of stocks in early 2021, this additional cost on buy orders largely disappears suggesting that collared orders incur higher trading costs.

Second, we use after hours trading data to exploit the sharp discontinuity at the 5% collaring policy cutoff. Using regression discontinuity analysis around this 5% threshold, we find significantly more high-cost trades occurring at or just below 5% compared to just above this level. This effect is economically meaningful, with over 40% more trades in the collared region. Placebo tests using alternative thresholds show no such discontinuity, confirming that the clustering of trades below 5% is driven by Robinhood's collaring policy rather than other factors.

Third, we exploit Robinhood's extension of the after-hours trading period on its platform. Up until March 29, 2022, after-hours trading on Robinhood ended at 6:00 PM. Beginning from this date, Robinhood extended the after-hours trading period to 8:00 PM. Using a difference-in-differences analysis comparing trading activity in the 4:00-6:00 PM versus 6:00-8:00 PM windows before and after the extension, we find a significant increase in high-cost trades during the newly extended Robinhood trading period. Our estimates suggest that the number of high-spread trades increased by more than 25% in the extended trading window after Robinhood implemented the change. This analysis provides additional evidence that Robinhood's collaring policy leads to more trades executing at extreme spreads.

Additionally, we supplement these findings with three supporting correlational analyses. First, we show a positive correlation between Robintrack popularity metrics and the frequency of high-spread retail trades. Second, there is a positive correlation between a stock's presence in the "Top Movers" section of the Robinhood app and the number of costly trades. Third, we quantify the losses resulting from high-spread trades during the after-hours period and correlate these losses with the Robinhood app's popularity, as measured by Google search trends over time.

Finally, we examine how prices exhibit extreme volatility due to the presence of the order collaring policy. Since retail traders are subject to excessive spreads up to 5% on each trade, correlated

retail trading on Robinhood (e.g., successive retail buys) may cause sudden price movements as strategic market makers know that their default orders will be converted to limit orders priced at a 5% differential over the prior transaction prices. Consequently, the order collaring policy can cause extreme price volatility as observed in *meme stocks* that are traded heavily by retail investors.

The current explanation of the unprecedented price volatility observed in January 2021 is primarily based on a short-squeeze theory. In their report, the SEC found that short covering, however, did not make up the majority of buying pressure during the GameStop (GME) price runup.[5] We investigate whether the order collaring policy could have also played a substantial role in these extreme price movements. Using Robinhood's after hours trading closure at 6:00 PM in January 2021 and the after hours trading extension in 2022, we find evidence that observed price volatility is higher when Robinhood traders exposed to order collaring have access to the market. Computing the volatility of transaction prices around the closure of Robinhood and its extension of the after-hours trading period, we find consistent evidence suggesting that the order collaring policy is potentially introducing extreme volatility to the observed prices.

To our knowledge, this is the first paper that examines the economics of order collaring. Our paper has important policy implications with regard to protecting retail investors, ensuring best execution, and reducing extreme volatility. First, one of the long standing missions of the SEC is to protect investors. Our findings regarding this previously unexplored retail broker practice may be valuable to policymakers at the SEC as we are able to quantify the potential cost of order collaring to retail investors. Given that this policy is advertised with the goal of protecting investors, it is important to inform regulators regarding its negative effects. Further, there are two more retail brokers, WealthSimple and DriveWealth, that employ similar order collaring practices, suggesting that this policy is not an isolated practice at a single retail broker.[6]

Relatedly, our analysis sheds light on how retail brokers, who are subject to the SEC and FINRA's duty of best execution, handle retail orders. The duty of best execution is a legal obligation requiring each retail broker to ensure that its clients' trades are executed in the most advantageous manner possible. [7] If the order collaring policy is harming retail investors, this would clearly

[5] https://www.sec.gov/files/staff-report-equity-options-market-struction-conditions-early-2021.pdf

[6] https://web.archive.org/web/20230326151246/https://help.wealthsimple.com/hc/en-ca/articles/360058451433

[7] The obligation for best execution comes from FINRA rule 5310, which states "in any transaction for or with a

conflict with the best execution duty.

Finally, our paper provides a novel mechanism in explaining the unprecedented extreme price movements observed in stocks with a high share of retail trading. Extreme price movements can lead prices to deviate significantly from fundamentals. Given that the default orders are subject to the order collaring during after-hours trading, extreme price movements are more likely. This prediction is consistent with the widespread price run-ups observed extensively in January 2021, specifically in extended-hours periods.

2. Related Literature

On the theoretical side, our paper is most closely related to Ait-Sahalia and Sağlam (2024) which examines the effect of an informative signal about the type of trader submitting a market order (patient or impatient) opposite the liquidity provided by a high-frequency market maker (HFMM). Patient traders are willing to pay a spread of δ whereas impatient traders are willing to pay a spread greater than δ to improve the likelihood of an execution. If the accuracy of the HFMM's signal improves, then the HFMM is better able to price discriminate among patient and impatient low frequency traders, exploiting the latter. In the model, this predatory quoting behavior leads to higher average bid-offer spread in the long-run equilibrium.

Our paper is related to the broad literature on order anticipation. Clark-Joseph (2013) examines whether HFTs use small trades to explore the price impact of E-mini futures for future exploitation. Bessembinder et al. (2016) studies the liquidity around predictable traders emerging from the rollovers of oil futures and do not find exploitative predatory trading. Sağlam (2020) finds that large institutional orders have higher trading costs if their execution leaves predictable patterns. Hirschey (2021) finds empirical evidence suggesting that high-frequency traders (HFTs) may increase the trading cost of non-HFTs by trading ahead of them. Battalio et al. (2024) find evidence that electronic liquidity providers increase the execution costs for large institutional investors through their order flow signals.

Our paper also contributes to the growing literature on the impact of retail trading on market

customer or a customer of another broker-dealer, a member and persons associated with a member shall use reasonable diligence to ascertain the best market for the subject security and buy or sell in such market so that the resultant price to the customer is as favorable as possible under prevailing market conditions." The full FINRA rule 5310 can be found at https://www.finra.org/rules-guidance/rulebooks/finra-rules/5310

quality. Eaton et al. (2022) use RobinTrack data to study the role of retail investors and find that Robinhood outages surprisingly lead to reduced price volatility and narrower quoted spreads. These findings suggest that, in general, Robinhood traders amplify market volatility through herding behavior. In contrast, Peress and Schmidt (2020) isolate news events that distract noise traders and show that reduced retail trading is associated with lower market liquidity. Our findings align with the increased price volatility linked to Robinhood's retail order flow, but we identify an additional mechanism—order collaring—that has not yet been explored in this area of the literature.

Barber et al. (2022) use Robinhood's 'Top Mover' list to demonstrate that retail traders tend to act in herds, and that specific herding events are often followed by negative stock returns. In particular, they show that Robinhood's app significantly influences investor behavior. For instance, the 'Top Mover' list contributes to herding behavior, where groups of retail traders buy the same securities simultaneously. Our paper, however, focuses on the substantial trading costs imposed on retail traders by Robinhood's order collaring policy.

Welch (2022) analyzes Robinhood investors' aggregate portfolio holdings using Robintrack data from 2018-2020 and finds that, contrary to popular perception, these investors' collective holdings were well-diversified and generated positive risk-adjusted returns. He also shows that Robinhood investors provided market stability during the COVID-19 crash by increasing their holdings after market declines. While Welch focuses on portfolio allocation and investment decisions, our analysis examines how Robinhood's order handling mechanisms affect retail traders' welfare through trading costs.

Fedyk (2022) explores the unique investing behaviors of users on the Robinhood trading platform, focusing on how they differ from those of previously studied individual investors. Using the Robintrack dataset, she finds that Robinhood users show a preference for investing in large, well-known companies that are going through difficult times, likely in anticipation of a rebound in stock price. On paper, portfolios representative of Robinhood users outperform the standard benchmarks, suggesting that these unconventional investment behaviors may have led to better-than-expected returns. However, due to lack of actual trade data, she does not quantify the real investment performance of the retail traders. Our findings suggest that even in the presence of such timing skill, the net investment performance of Robinhood investors can be significantly lower because of the higher trading costs associated with the order collaring policy.

Finally, our paper contributes to the recent focus on identifying retail order flow from publicly available trade data. Based on dark subpenny trades, Boehmer et al. (2021, BJZZ) propose an algorithm to identify retail trades. Barber et al. (2024) generate retail trades using retail broker APIs and find that the BJZZ algorithm can only capture about one-third of these retail trades. Additionally, Battalio et al. (2023) examine direct wholesaler and institutional broker trade data, showing that the BJZZ algorithm is not only limited in its ability to capture retail trades, but it also classifies some institutional trades as retail. In this paper, we find that subset of Robinhood trades during extended hours can be also identified by utilizing the platform's order collaring logic.

3. Institutional Details

3.1. Overview

Robinhood, founded in 2013, was the first retail brokerage to enable commission-free trading for retail traders. Without commissions, Robinhood's main revenue source is PFOF, which is a practice where a brokerage receives compensation from a wholesaler, such as Citadel Securities or Virtu Financial, in exchange for directing its clients' orders to that wholesaler for execution. Typically, these orders are executed at the far side of the spread with some de minimis price improvement over the best available prices (with round lots) displayed on public exchanges. Since retail orders are expected to be uninformed, wholesalers can profit from internalizing them as they experience less adverse selection costs. Uninformed orders allow wholesalers to pocket a big fraction of the bid-ask spread over the long-run.

PFOF has been a controversial topic because it creates a potential conflict of interest, as the broker may have an incentive to prioritize its own financial interests over those of its clients (Battalio et al., 2016). However, it is also argued that payment for order flow can benefit individual investors by providing them with faster and more efficient order execution as well as reduced costs in the form of brokerage fees (i.e., commission-free trading). Regarding the financial incentives of retail brokerages, they generate more revenue when their clients trade more frequently, rather than when their clients obtain the best available price for their orders.

Since trades from retail brokers are almost entirely routed through wholesalers, they are reported through the FINRA trade reporting facility (TRF), identified by the exchange code 'D'. We will

extensively use this exchange code to filter the trades, as the majority of Robinhood orders are executed by wholesalers in off-exchange venues.

3.2. Robinhood User Interface and Trade Execution

To gain a full understanding of Robinhood's trade execution practices, it is important to understand the user experience in their mobile application. First, the retail client has to choose between two default options: a share-based and dollar-based order. In a dollar-based order, retail traders specify the dollar amount they wish to invest, and Robinhood calculates the equivalent number of shares, potentially in fractional amount. Alternatively, traders can choose to send a share-based order, where they specify the exact number of shares (i.e., no fractional amount) they want to buy or sell. The user interface workflow for share-based and dollar-based orders is very similar. In both cases, the user can submit her order in 4 screens: (i) specify the ticker of the security, (ii) choose to buy or sell, (iii) specify the amount in number of shares or dollar amount, and (iv) review and submit the order by swiping up. Figure A.1 in the Online Appendix illustrates these steps in each screenshot for a share-based order.

There are additional complex order types referred to as "Conditional Orders" available as well. For example, the user interface workflow for a conditional order type, limit order, can be seen in Figure A.2. In this case, where a trader wants to submit a standard limit order by designating her own limit price, she must navigate through 9 screen-steps, which is *125% more* than the steps required for default share-based or dollar-based orders. Thus, the additional steps suggest that Robinhood is encouraging their retail customers to use their default order types which may be subject to collaring. Additionally, unlike the default dollar- and share-based order types, Robinhood does not save the "Conditional Order" screen as a starting interface. This means that when a trader returns to the platform to place another trade, they must go through the entire process again, including re-selecting the desired order type. This again implies that Robinhood wants their retail customers to submit a default order that may be subject to order collaring.

3.3. Robinhood's trading hours and order collaring policy

When an order is subject to order collaring, to compute the collared limit order price, Robinhood uses the last transaction price on a NASDAQ exchange (the NASDAQ Stock Market, NASDAQ

OMX BX, or NASDAQ OMX PHLX) at the time of order submission.[8]

Table 1 shows the time intervals of trading sessions and the various collaring cases that Robinhood utilizes for different order types. During regular market hours, share-based buy orders, but not sell orders, are subject to collaring. Neither dollar-based buy or sell orders are collared during this period. In contrast, all order types are subject to collaring in the pre-market and after-hours trading sessions. Our analysis will specifically examine the asymmetric implementation of order collaring during regular trading hours with regard to share-based buy and sell orders.

Up until March 29, 2022, after-hours trading on the Robinhood platform ended at 6:00 PM. Beginning from this date, Robinhood extended the after-hours trading period to 8:00 PM. In the following analyses, we will make use of both of these features. Since Robinhood is not active after 6:00 PM before March 29, 2022, we do not expect Robinhood's order collaring practice to have any impact between 6:00 PM and 8:00 PM. Similarly, we will also utilize the extension of the after-hours trading to 8:00 PM on March 29, 2022 as another positive shock to order collaring.

3.4. Motives for order collaring

Robinhood states that "...to help protect our customers from potential price volatility, Robinhood automatically converts most market orders into limit orders using a 5% price collar."[9] However, given the various features of the order collaring policy explained in the previous section, it is important to consider some alternative motivations.

There are potentially four reasons for this 5% collaring rule. First, consistent with the stated motive, if the bid-ask spread exceeds 10% (e.g., during extended-hours trading sessions), setting a limit at 5% over a prior transaction price can help Robinhood protect its users from executing trades when the bid-ask spread is extremely high. However, it is unclear whether this is an effective protection mechanism in such high-spread setting, as the order is still subject to a 5% markup compared to a recent transaction. This represents a significant trading cost that may deter any sophisticated investor from trading at that time.

Second, given that buy orders are collared while sell orders are not during regular market hours,

[8] http://web.archive.org/web/20230523174429/https://robinhood.com/us/en/support/articles/limit-order/

[9] https://web.archive.org/web/20221208173112/https:/robinhood.com/us/en/support/articles/market-order/

collaring seems to be utilized as a risk management strategy. By collaring buy orders, Robinhood aims to ensure that clients have sufficient capital to cover the trade, given that the transaction price of a market order can be uncertain, potentially due to significant latency in Robinhood's order submission technology. This alternative explanation is further supported by the warning screen that comes up in the Robinhood trading platform if a trader does not have enough capital to transact at the limit price set by the 5% order collaring rule.[10]

Third, collaring could increase the likelihood of a trade getting filled during extended-hours sessions, increasing Robinhood's PFOF revenue. Typically, brokers do not allow their customers to use market orders in these sessions due to low liquidity. But with Robinhood's order types having a large collar of 5%, there is an increased probability of a trade getting filled regardless of high spreads. Further, a collared trader's willingness to pay a 5% premium above the last trade can represent impatience exploitable by strategic market makers. Given that Robinhood's main source of revenue is PFOF, this policy may increase payment frequency and order flow value. Based on 2020 SEC filings, Robinhood had the highest payment per 100 shares executed.[11]

Finally, fractional revenue from collared orders could be another alternative motive since Robinhood trades fractional orders on a principal basis. In this case, it is lucrative to fill the collared order with a high spread over the prior transaction price. This motive seems less likely though as during regular market hours, such orders are not collared.

4. Data

4.1. Data sources

We compile our dataset from seven sources. Our transaction and quote data came from the NYSE Trade and Quote (TAQ) database. We use the Center for Research in Security Prices (CRSP) to obtain daily firm-level data such as close prices, share volume, shares outstanding and share code. We obtain the number of Robinhood users holding a particular security from the Robintrack dataset which is available between May 2018 and August 2020. To get a glimpse into limit order

[10] If you have exactly $100 in your Robinhood account and attempt to buy one share of the stock with the most recent traded price of $100, you will receive a warning stating, "Not Enough Buying Power: Because this order has a maximum cost of $105, you don't have enough buying power in your account to place this order."

[11] https://www.cnbc.com/2020/08/13/how-robinhood-makes-money-on-customer-trades-despite-making-it-free.html

book behavior, we utilize a sample Level 2 order book data (Integrated Data Feed) disseminated by WRDS covering NYSE and ARCA exchanges on October 4, 2021 and October 5, 2021. We use WRDS Consolidated Trade (WCT) dataset to match trades with NBBO quotes. We use Millisecond Intraday Indicators by WRDS for stock-day level trading activity measures. Finally, we use Rule 605 disclosures from wholesalers to identify stocks with high and low retail trading activity.

4.2. Data construction

Robinhood explicitly states that they collar orders based on the last transaction price on a NASDAQ exchange. To identify NASDAQ trades, we use exchange codes T, Q, B, and X.[12]

We use sale condition flags to eliminate irregular trades. Specifically, trades with sale condition 'M' (market center close price) and 'Q' (market center open price) are filtered out because they are status messages from the NYSE not real trades. In the extended hours session, we ensure all trades have sale condition 'T' which is an official flag to identify an extended hours trade. Finally, in order to remove out-of-sequence trades, we exclude trades with sale conditions 'Z' (out-of-sequence sold trade), 'U' (out-of-sequence-trade in extended hours), 'N' (next-day clearing trade), and 'P' (trade with prior reference price). To ensure there are no erroneous trades included, we only include trades with trade correction indicator '00' which refers to a regular trade which is not corrected or changed.

Finally, we primarily use U.S. common stocks with share code 10 or 11 in our main analyses and also provide robustness tests using all securities including ETFs. To eliminate significant trading activity in low-priced stocks, we require a closing price of greater than or equal to $1. To mitigate potential effects from fractional trading, we require trade size to be greater than 1 share.[13]

4.3. Trading cost measures

In this section, we describe the cost measures that are used to examine the impact of the order collaring policy on retail trading costs. We employ two spread-based measures and one count-level

[12]The 'T' exchange code corresponds to the NASDAQ Stock Exchange (in Tape A, B securities). The 'Q' exchange code corresponds to the NASDAQ Stock Exchange (in Tape C securities). The 'B' exchange code corresponds to the NASDAQ OMX BX exchange. The 'X' exchange code corresponds to the NASDAQ OMX PSX exchange. These classifications are taken directly from the NYSE TAQ documentation: https://www.nyse.com/publicdocs/nyse/data/Daily_TAQ_Client_Spec_v3.0.pdf

[13]Our findings are robust to removing any of these filters.

measure to quantify the impact of order collaring policy on retail trading costs.

Since the order collaring policy uses the last transaction price on a NASDAQ exchange to compute the collared limit price, our first spread-based measure is defined using this benchmark. For a transaction on stock i at time t, we compute

$$NasdSpd_{i,t} = q_{i,t}\frac{P_{i,t} - NP_{i,t}}{NP_{i,t}}, \tag{1}$$

where $NP_{i,t}$ denotes the last NASDAQ transaction price preceding this trade, and $q_{i,t}$ equals 1 for buy trades and -1 for sell trades. We use the Lee-Ready algorithm to sign the trades as buy or sell. We will use *NasdSpdB* and *NasdSpdS* to denote the measure for buy and sell trades separately. To compute an aggregate measure at the daily level, we will use *AvgNasdSpd*, (*AvgNasdSpdB* and *AvgNasdSpdS*) by computing a share-weighted average of *NasdSpd* (*NasdSpdB* and *NasdSpdS*) in the same time period.

Finally, to measure the frequency of high-spread retail trades, we will count the number of D-exchange trades that have their *NasdSpd* falling within a large range in a given period. Specifically, a trade is a high-NASDAQ-spread (*HNS*) trade if it has a *NasdSpd* between 1% and 5%. Note that if a trade has a *NasdSpd* greater than 5%, the order leading to the trade cannot be originating from Robinhood.

4.4. Summary statistics

In this section, we report summary statistics in two parts based on our two different analyses: regular trading hours and after-hours trading activity.

4.4.1. Summary statistics from regular trading hours

In our analysis of regular trading hours, we primarily use common stock data from April 2020 to December 2020, a period characterized by elevated levels of retail trading due to work-from-home regulations associated with the COVID-19 pandemic.

Table 3 reports summary statistics for all common stocks traded during regular trading hours in our sample period. This table shows that close prices in our sample vary from $1.00 to $4,446.88, with an average of $50.02. Market capitalizations span from $2 million to $2.3 trillion, averaging

$9.63 billion, while the daily dollar volume of trades ranges from $15 to $68.37 billion, averaging $75.6 million. D-exchange transactions constitute 36.55% of dollar volume and 25.54% of trades. The total number of trades varies from 1 to 2,843,775, with an average of 11,217. Share volume averages 1.49 million shares, with D-exchange volume representing 36.55%. Turnover rates range from 0% to 6901%, averaging 1.91%. Buy (sell) orders make up 49.01% (50.99%) of trades, with similar D-exchange buy/sell percentages at 49.11%/50.89%. *AvgNasdSpd* shows significant variation, from -1,308 to 2,226 basis points for buy trades and from -2,026 to 2,208 basis points for sell trades. The average *AvgNasdSpd* is 20.0 basis points for buy trades and 18.9 basis points for sell trades, with median values of 7.3 and 7.0, respectively.

4.4.2. Summary statistics from after-hours trading period

In our analysis of after-hours trading data, we will primarily make use of the number of *HNS* trades in the dark, as defined in Section 4.3.

Table 4 reports summary statistics on the dark *HNS* trades in the after-hours trading period. In each panel, we compare various statistics of these dark trades between two periods: low retail trading in 2014–2019 and high retail trading in 2020–2022.

There are several interesting implications from the panels in Table 4. First, we find that in the retail-heavy period between 2020 and 2022, the frequency of these dark *HNS* trades increases by an order of magnitude compared to the earlier period. We observe that there are more than $3,300$ *HNS* trades in the dark on average per trading day compared to under 400 per day in the prior period. Consistent with this increase, we also see an increase in the frequency of odd-lot trades in this period. The share of odd-lot trades increase from 39% to almost 60%. Overall, these statistics indicate a significant association between the increase in dark *HNS* trades and the rise in retail trading activity in the post 2020 period.

5. Evidence from the asymmetric implementation of the order collaring during regular trading hours

In this section, we exploit the asymmetric implementation of Robinhood's order collaring policy during regular market hours to provide empirical evidence that it increases trading costs. As shown

in Table 1, during regular market hours, retail buy orders are subject to collaring while sell orders are not.

5.1. Visual evidence from NYSE Limit Order Book

Do strategic traders react to this order collaring mechanism? To answer this question, we first utilize a sample Level 2 order book data (Integrated Data Feed) disseminated by WRDS covering NYSE and ARCA exchanges on October 4, 2021 and October 5, 2021. From Table 1, we know that, during regular trading hours, Robinhood buy orders are collared while sell orders are not. If strategic traders are trying to exploit these high-spread trades, we should find empirical evidence of limit sell orders being placed to meet Robinhood buys at or close to the 5% spread level. Given that Robinhood does not collar sell orders during regular trading hours, our conjecture is that there would be more limit sell order clustering around 5% compared to buy orders in the limit order book.

Figure 1 summarizes our findings. In the top panel, we illustrate the spread of orders (with an ADD message) over the last NASDAQ trades for a retail heavy stock, Virgin Galactic (SPCE). When comparing buy orders versus sell orders, we find results consistent with our expectation. Buy orders from strategic traders do not show clustering at 5%. However, sell orders show noticeable clustering exactly at 5%.

The bottom panel in Figure 1 extends this analysis to all securities including ETFs. In this extended universe, we find that the collection of all added sell orders cluster around 5% while the added buy orders do not. This is again consistent with the order anticipation channel. One significant problem with the order collaring policy is that it affects not just common stocks but all exchange-traded products, including ETFs. Therefore, this visual evidence implies that the scope of the policy is even larger when you account for the extended universe of securities.

5.2. Evidence from the *NasdSpd* of buy and sell trades

Does order collaring impact market quality and trading costs? During regular market hours, share-based market buy orders coming from Robinhood will be subject to 5% collaring while market sell orders are not subject to any collaring. Therefore, we expect that retail buy trades will be more likely to have a larger *NasdSpd* because wholesaler-linked market makers in public exchanges will

potentially determine their bid and ask quotes by considering this profitable order flow coming from Robinhood.

For this analysis, we take all the dark trades from April to December 2020 occurring on common stocks. We then classify each dark trade as a buy or sell using the Lee-Ready algorithm and compute its *NasdSpd* using equation (1). We then compute the daily metric, *AvgNasdSpd*, for each stock and trade direction (i.e., buy or sell) by calculating the share-weighted average.

In our analysis, we use stocks with high (low) retail activity as the pseudo-treatment (pseudo-control) group. We use two methods to determine the stocks in these two groups: (i) BJZZ algorithm and (ii) Rule 605 disclosures. The BJZZ algorithm identifies retail trades by examining sub-penny execution prices for dark trades. If P_{it} is the transaction price of the dark trade in stock i at time t, let $Z_{it} \equiv 100 * \text{mod}(P_{it}, 0.01)$, which represents the fraction of a penny in the trade price. BJZZ classifies a trade as retail if $Z_{it} \in \{(0, 0.4) \cup (0.6, 1)\}$. For each trading day, we then rank all common stocks by their percentage of trading volume from retail trades and assign stocks in the top (bottom) quintile to the pseudo-treatment (pseudo-control) group.

The BJZZ algorithm captures approximately 30% of total retail trading activity based on the analyses by Barber et al. (2024) and Battalio et al. (2023). However, since we use the algorithm to create relative rankings rather than to identify absolute levels of retail trading, our methodology is less sensitive to the limitations of the algorithm. Nevertheless, to ensure robustness of our results, we also employ monthly Rule 605 disclosures as an alternative classification method. Following Dyhrberg et al. (2022), we aggregate Rule 605 data across the eight major wholesalers (Citadel, Virtu, G1, Jane Street, Two Sigma, UBS, Merrill Lynch, and Morgan Stanley) to construct a retail trading activity measure at the stock-month level. For each trading day within a given month, we then assign stocks in the top (bottom) quintile of retail activity to the pseudo-treatment (pseudo-control) group.

Let $AvgNasdSpd_{i,t,k}$ be the share weighted spread from the last NASDAQ transaction price for stock i on day t, and for direction $k \in \{buy, sell\}$. $Buy_{i,t,k}$ is a binary variable that takes a value of 1 (0) if k refers to buy (sell) orders. $TopRetail_{i,t}$ is a binary variable taking a value of 1 (0) if stock i is in the top (bottom) quintile of retail trading activity on day t, where retail activity is measured using either the BJZZ algorithm or Rule 605 disclosures.

We run the following linear regression to quantify the impact of the order collaring policy on

these intraday spreads:

$$AvgNasdSpd_{i,k,t} = \beta_1 Buy_{i,k,t} \times TopRetail_{i,t} + \beta_2 Buy_{i,k,t} + \beta_3 TopRetail_{i,t} + \sum_j \delta_j ControlVar_{i,t} + \mu_i + \mu_t + \epsilon_{i,k,t}. \quad (2)$$

We use absolute daily return, turnover, the fraction of buy orders, and the logarithm of market capitalization at close price as control variables and include stock and day fixed effects as denoted by μ_i and μ_t. Standard errors are clustered at the stock-day level.

Tables 5 and A.2 report the regression results using BJZZ algorithm and Rule 605 disclosures, respectively, to identify stocks with high and low retail trading activity. In all specifications, the coefficient on *Buy* × *TopRetail* is positive and statistically significant implying that compared to the low retail activity control group, buy trades have larger *NasdSpd* when the stock is traded heavily by retail traders. The economic magnitude of the coefficient, ranging from 3.6 to 3.8 basis points, is also significant when compared to the reported mean and median values of *AvgNasdSpdB* and *AvgNasdSpdS* in Table 3. Compared to the mean (median) values, this implies a percentage increase of more than 18% (49%). Overall, the results are consistent with the hypothesis that order collaring increases retail trading costs.

5.2.1. Robustness using trade data before fractional trading and COVID-19

As we noted earlier in the discussion of order types, Robinhood offers two types of default buy orders: dollar-based and share-based. Share-based buy orders are subject to collaring, while dollar-based buy orders are not. Our data does not allow us to distinguish between these two order types, nor can we determine the proportion of Robinhood buy orders that fall into each category. However, it is important to note that dollar-based orders were not available until Robinhood introduced fractional share trading in December 2019.[14] To confirm the robustness of our findings, we re-run the regression specified in equation (2) using all intraday dark trades from January 2019 to November 2019, a period when all Robinhood buy orders were share-based and thus collared during regular trading hours. As shown in Table A.3 in the Online Appendix, the coefficient on *Buy* × *TopRetail* remains significant with similar economic magnitude.

[14] https://www.cnbc.com/2019/12/12/robinhood-joins-a-wave-of-fractional-stock-trading-offers.html

This analysis provides two robustness checks. First, it confirms that our findings are not solely attributable to increased retail trading during the COVID-19 pandemic. Second, it demonstrates that even before the introduction of dollar-based order types, retail trading costs were abnormally high for collared buy orders after controlling for stock-level and market-level conditions.

5.3. Evidence from Robinhood trading restrictions in early 2021

On January 27th, 2021, during the peak of the meme stock frenzy, the National Securities Clearing Corporation (NSCC) notified Robinhood of a $693 million end-of-day deposit requirement. Unable to meet this requirement, Robinhood attempted to reduce volatility by restricting 13 securities to position-closing-only (PCO) on January 28th, 2021.[15] In subsequent days, the company imposed purchase limitations on up to 50 securities identified as contributing to the elevated NSCC deposit requirement. These restrictions remained in effect, in various forms, until February 5th, 2021. Table 2 provides a detailed timeline of Robinhood's restrictions.

We use these trading restrictions as a natural experiment to extend our analysis from Section 5.2, which shows that buy orders on stocks with high retail activity face higher spread costs compared to sell orders on the same stocks due to the asymmetric implementation of order collaring. Since PCO restrictions and purchase limitations prevented Robinhood accounts from executing buy-side trades in restricted securities, we expect the additional cost on buy orders to dissipate during the restriction period due to the absence of order collaring.

We analyze all dark trades during regular market hours in January and February 2021, focusing on a subsample of stocks with high retail activity (those in the top quintile of retail trading volume based on the BJZZ algorithm). Let $AvgNasdSpd_{i,t,k}$ be the share weighted spread from the last NASDAQ transaction price for stock i on day t, and for direction $k \in \{buy, sell\}$. $Buy_{i,t,k}$ is a binary variable that takes a value of 1 (0) if k refers to buy (sell) orders. $Restriction_{i,t}$ is a binary variable taking a value of 1 (0) if i refers to a stock that Robinhood restricted on day t. We run the following linear regression to quantify the impact of Robinhood trading restrictions on these

[15] See page 72 of the 'GameStopped' report prepared by the majority staff of the Committee on Financial Services, U.S. House of Representatives. https://democrats-financialservices.house.gov/uploadedfiles/6.22_hfsc_gs.report_hmsmeetbp.irm.nlrf.pdf

intraday spreads:

$$AvgNasdSpd_{i,k,t} = \beta_1 Buy_{i,k,t} \times Restriction_{i,t} + \beta_2 Buy_{i,k,t} + \beta_3 Restriction_{i,t} + \sum_j \delta_j ControlVar_{i,t} + \mu_i + \mu_t + \epsilon_{i,k,t}. \tag{3}$$

We use absolute daily return, turnover, the fraction of buy orders, and the logarithm of the market capitalization at close price as control variables and include stock and day fixed effects as denoted by μ_i and μ_t. Standard errors are clustered at the stock-day level.

Table 6 reports the regression results. In all specifications, the coefficient on *Buy* × *Restriction* is negative and statistically significant, indicating that the buy-side asymmetry in *NasdSpd* for high retail activity stocks decreases during Robinhood trading restrictions. The economic magnitude of this effect is substantial: the coefficient of −3.76 basis points, when compared to the *Buy* coefficient of 4.90 basis points, indicates that trading restrictions reduce the buy-side asymmetry in *NasdSpd* by approximately 76%. The positive and significant coefficient on *Buy* is expected, as our sample consists exclusively of stocks with high retail activity. These results support our hypothesis that Robinhood's PCO restrictions and purchase limitations mitigate the elevated trading costs induced by order collaring, as documented in Section 5.2.

6. Evidence from trading activity after market close

In the previous sections, we provided empirical evidence that order collaring substantially increases retail trading costs during regular trading hours. In the following sections, we shift our focus to after-hours trading. Outside of regular market hours, stocks are less liquid and Rule 605 is not enforced. Together these factors lead to larger bid-ask spreads. One important advantage of examining the after-hours period is that all default order types, share- or dollar-based and buy or sell, are collared during this time. This creates an effective experimental setting for us to present multiple pieces of evidence that the number of *HNS* trades during the after-hours period is causally related to Robinhood's order collaring policy.

We have two identification strategies for our causal evidence. First, we utilize the sharp discontinuity around the 5% limit defined in the order collaring policy. Second, we examine the extension

of the after-hours trading session on the Robinhood app. Additionally, we supplement these findings with three supporting correlational analyses. First, we demonstrate a positive correlation between Robintrack popularity metrics and the number of *HNS* trades. Second, we find a positive correlation between the likelihood of being listed in the "Top Movers" section of the Robinhood app and the number of *HNS* trades. Lastly, we quantify the losses caused by these *HNS* trades during the after-hours period and correlate these losses with the popularity of the Robinhood app as indicated by Google search trends over time.

6.1. Sharp discontinuity around 5% level and Robinhood's closure time

As defined by Robinhood's order collaring rule, we know that collared trades coming from Robinhood cannot be executed above a 5% spread from the most recent NASDAQ transaction. Therefore, if Robinhood's order collaring policy causes its users to trade at high-cost spreads, we should observe more frequent trades just below the maximum 5% spread than we observe just above that threshold. Further, before March 29, 2022, Robinhood's after-hours trading period ended at 6:00pm which allows us to compare the number of *HNS* trades being executed in the short interval just before 6:00 PM (Robinhood open) and just after 6:00 PM (Robinhood closed).

6.1.1. Visual evidence

The top panel in Figure 2 illustrates all *HNS* trades in April 2019 with a *NasdSpd* of approximately 5% during the sixty minutes before and after 6:00 PM. The bottom panel in Figure 2 plots the same activity for April 2020.

First, we observe that the number of trades that occur exactly at a 5% spread is significantly higher in the pre-closure period (before 6:00 PM). Specifically, a 5% *NasdSpd* is the most frequently occurring value (mode) in both months. Similarly, in both plots, there are almost no trades which have a *NasdSpd* of just above 5% while there is a large cluster of trades that occur right below this threshold. When compared to the post-closure period during which Robinhood trading platform is closed, these patterns seem quite abnormal. Overall, both plots provide a striking visual evidence that Robinhood's order collaring can cause a significant increase in dark trades with large *NasdSpd*.

6.1.2. Regression analysis

In this section, we provide a formal regression discontinuity design to establish the causal impact of order collaring on the number of costly retail trades. We focus on the discontinuity around the 5% *NasdSpd* threshold, which is the maximum spread that the order collaring rule uses. Specifically, our assumption is that any differences in the number of costly retail trades on either side of the 5% cutoff should be only due to Robinhood's order collaring policy.

Let $NumHCT_{k,t}$ measure the number of high-cost trades in the dark on day t between 4:00 PM and 6:00 PM (across all common stocks) in two spread categories indexed by $k \in \{0, 1\}$. $NumHCT_{0,t}$ is the number of trades in the treatment region where *NasdSpd* lies in the interval $[5\% - s, 5\%]$ and s is the bandwidth choice. Similarly, $NumHCT_{1,t}$ is the number of trades in the no-treatment category where *NasdSpd* falls in $(5\%, 5\% + s]$. Finally, let $Treat_{k,t}$ be equal to 1 if k is 0 and 0 otherwise. Following Cohn et al. (2022), we run the following Poisson regression to quantify the impact of the order collaring policy on the number of high-cost trades:

$$\begin{aligned} \text{NumHCT}_{k,t} \mid \mathbf{x_{k,t}} &\sim \text{Poisson}(\lambda_{k,t}), \\ \log(\lambda_{k,t}) &= \alpha + \beta_1 \, Treat_{k,t} + \sum_j \delta_j \, ControlVar_{j,k,t}. \end{aligned} \tag{4}$$

Panel A of Table 7 illustrates the regression results with different bandwidth choices ($s \in \{0.05\%, 0.1\%, 0.25\%\}$) and time-periods (January 2014 – March 2022 or Janaury 2020 – March 2022). In all specifications, the coefficients coefficient on *Treat* are positive and statistically significant implying that there are more high-cost trades occurring at or just below the 5% threshold. The coefficients are also economically significant. The number of high-cost trades in the collared region increases by at least 32% compared to the non-collared region.[16] This effect remains economically robust across different bandwidth specifications and during the COVID period, reaching up to approximately 48%.

Our results remain qualitatively unchanged even when excluding trades that occur exactly at the 5% threshold from our analysis. Therefore, our findings are not influenced by a higher tendency to submit orders at a round spread value of 5%. Further, to verify that the regression discontinuity design is not obtaining spurious estimates of the effects of order collaring, we conduct a placebo

[16] We compute this additional effect with $e^{\beta_1} - 1$ where β_1 is the coefficient on *Treat*.

test exploiting an alternative threshold at 7%. Panel B of Table 7 illustrates the corresponding regression results using the same bandwidth choices and time-periods. In all specifications, the coefficients on *Treat* are insignificant.

6.2. Evidence from Robinhood's extension of the after-hours trading period

On March 29, 2022, Robinhood extended their after-hours trading session from 4:00-6:00 PM to 4:00-8:00 PM. We employ a difference-in-differences regression to examine the impact of Robinhood's order collaring on the number of costly retail trades around this shock.

6.2.1. Visual evidence

The top panel of Figure 3 illustrates all high-cost dark trades in March 2022 before the extension date, March 29, 2022. Similarly, the bottom panel in Figure 3 illustrates all high-cost dark trades in April 2022 which is the first month after the extension. In both panels, we plot the trades having a *NasdSpd* between 2% and 7%. These plots provide another piece of striking visual evidence that Robinhood's collaring policy leads to retail trades executing at high absolute spreads compared to the most recent NASDAQ trade. Relative to the top panel in which Robinhood is not active after 6:00 PM, the bottom panel suggests that the number of trades occurring at or just below the 5% threshold increases substantially after 6:00 PM after the extension date.

6.2.2. Diff-in-Diff analysis

We now formally examine the effect of the extension on the number of *HNS* trades using a difference-in-differences methodology. If order collaring leads to an increase in costly trades, then after controlling for the overall trend in trades with high *NasdSpd*, we should observe an increase in the number of costly retail trades after 6:00 PM in the post-extension period compared to the pre-extension period.

Formally, let $NumHCT_{t,k}$ measure the number of trades with a *NasdSpd* between $5\% - s$ and 5% on day t in the control (treatment) period where $k = 1$ ($k = 2$) denotes the trading window between 4:00 PM and 6:00 PM (6:00 PM and 8:00 PM). Finally, let $Post_{t,k}$ be equal to 1 if t is later than March 29, 2022 and 0 otherwise. We use equal number of days for the pre- and post-window by using 42 business days around the effective extension date. We then run the following Poisson

regression with various s values to quantify the impact of the order collaring policy on the number of trades with high *NasdSpd*:

(5) $\text{NumHCT}_{t,k} \mid \mathbf{x_{t,k}} \sim \text{Poisson}(\lambda_{t,k})$,

$$\log(\lambda_{t,k}) = \alpha + \beta_1 Post_{t,k} \times After6PM_{t,k} + \beta_2 After6PM_{t,k} + \beta_3 Post_{t,k} + \sum_j \delta_j ControlVar_{j,t,k},$$

where $After6PM_{t,k}$ takes a value of 0 (1) if $k = 1$ ($k = 2$). We again adjust our standard errors by clustering at the calendar day level.

Table 8 presents the regression results for various values of s chosen from the set $\{4\%, 3\%, 2\%, 1\%, 0.5\%\}$. In all specifications, the coefficients on $Post \times After6PM$ are positive and statistically significant implying that after controlling for the overall time-series effect by tracking the activity between 4:00 PM and 6:00 PM, the number of trades having extreme *NasdSpd* has increased after the extension of the Robinhood's after-hours trading session. The coefficients are also economically significant. The coefficients on the interaction term ($Post \times After6PM$) show that the number of high-cost trades in the 6:00-8:00 PM window increased by at least 24.6% ($e^{0.22} - 1$) after the extension, with the effect becoming substantially stronger for trades closer to the 5% spread threshold, reaching a 169% increase ($e^{0.99} - 1$) for spreads between 4.5% and 5%.

6.3. Evidence from Robintrack and Robinhood's "Top Movers" List

In this section, we provide supporting correlational analysis that *HNS* trades are most likely originating from Robinhood. For this analysis, we complement our after-hours trading data with Robintrack popularity metrics which is available between May 3, 2018 and August 5, 2020. We use a similar measure to proxy for the level of *HNS* trades at the stock-day level. Let $NumHCTs_{i,t}$ be the number of *HNS* trades in stock i on day t between 4:00 PM and 6:00 PM.

From mid-2018 to mid-2020, Robinhood offered an API that made it possible to obtain the number of (anonymous) Robinhood investors who held a particular stock at that particular moment. Robintrack.net scraped this data and created a data set of the number of individual accounts holding each stock throughout the day. Using this data set, we track the number of accounts holding particular securities to create a sample of stocks that are traded or held most by Robinhood users.

Additionally, Robinhood displays a "Top Movers" list which includes 20 stocks having largest

absolute percentage return since the market close the prior day. If *HNS* trades originate from Robinhood users, we anticipate observing a higher frequency of such trades on stocks listed in the "Top Movers" list. Likewise, we would expect to observe a greater number of *HNS* trades on a stock that is widely held or actively traded by Robinhood users. To test these hypotheses, we define the following variables: $Top20Mover_{i,t}$ is an indicator variable taking a value of 1 if stock i is one of the 20 stocks having the largest absolute percentage return between day $t-1$ and t, $TopHeld_{i,t}$ is an indicator variable taking a value of 1 if the stock i is included in the top 5% of all securities with regard to the number of accounts holding it on day t and $TopTraded_{i,t}$ is an indicator variable taking a value of 1 if stock i is included in the top 5% of all securities with regard to the sum of absolute changes in the accounts holding it on day t. We then estimate the following Poisson regression model:

$$\text{NumHCTs}_{i,t} \mid \mathbf{x_{i,t}} \sim \text{Poisson}(\lambda_{i,t}),$$
$$\log(\lambda_{i,t}) = \beta_1 Top20Mover_{i,t} + \beta_2 TopHeld_{i,t} + \beta_3 TopTraded_{i,t} + \sum_j \delta_j Control_{j,i,t} + \mu_i + \mu_t, \tag{6}$$

where we control for the turnover in regular market hours and extended hours period, logarithm of the market capitalization, and absolute daily return along with stock and day fixed effects. Standard errors are clustered at the stock-day level.

Table 9 presents the regression results. We find that all three Robinhood order flow proxies are positively correlated with the number of high-cost trades, as indicated by the positive and statistically significant coefficients β_1, β_2, and β_3 in the first three columns. For instance, if a stock appears on Robinhood's "Top Movers" list on a given day, the expected number of *HNS* trades is approximately 4.9 times as large as that of a stock not included in this list. Similarly, if a stock is among the most traded stocks by Robinhood users on a given day, the expected number of *HNS* trades is about 4.8 times as large, all else being equal. When we include all three proxies in the regression, the coefficients on *Top20Mover* and *TopTraded* remain both statistically and economically significant, suggesting that these high-cost dark trades originate from the Robinhood platform.

6.4. Total cost of the order collaring policy in after-hours trading and its relation to Robinhood's popularity

In this section, we compute the total loss of the *HNS* trades in the after-hours trading by comparing the percentage deviation between their execution prices from the close price realized at 4:00 PM. For example, if a two-share buy trade occurs on a security for $102 while its close price is $100, then we record this trade as having a $4 loss. We define this statistic to be close-price-based loss markup. To eliminate any bias from earnings announcements or other corporate announcements, we compute this statistic for a tight interval between 5:45 PM and 6:00 PM during which the Robinhood platform is always open.

The top panel in Figure 4 plots the total dollar volume of trades occurring in this 15-minute interval before 6:00 PM. In the bottom panel, the solid black line plots the monthly dollar loss of *HNS* trades benchmarked to close prices. If the total loss value were independent of Robinhood user activity, we would expect to see a high correlation between dollar volume and the total loss across time as some constant fraction of all trades can have a high spread for idiosyncratic reasons. However, we find that this correlation is pretty low, namely 42%. While the losses peak during the meme stock period in January 2021, the total dollar volume in this interval does not exhibit any major spikes.

The red dashed line in both panels of Figure 4 plots the relative Google search interest for the keyword "Robinhood." The values are normalized according to maximum value achieved in January 2021. Search interest on the company remains constant up until the COVID period in March 2020 from where the search volume goes up dramatically. The highest interest is around the meme-stock period.

Compared to the dollar volume series in the top panel, this proxy for the popularity of the Robinhood trading platform explains the variation in the total loss markup with a much better fit. Consistently, the correlation between the normalized search counts and the total loss increases to 85%. This high correlation is achieved despite the obvious limitations of the normalized count measure. For example, in January 2021, the search counts likely peaked due to the platform's newsworthiness during the meme-stock frenzy. Overall, this visual evidence provides further support for the link between retail traders' aggregate losses and the order collaring policy, as well as the large

economic impact of these aggregate losses. Despite examining a very short interval of 15 minutes every day, the aggregate retail losses reach up to $35 million in a month, with an average value of $6 million in our sample period.

7. Order collaring and extreme price movements

In this section, we examine the relation between excessive volatility and Robinhood's order collaring policy.

7.1. Visual Evidence from Gamestop Price Run-up

We first provide visual evidence of the impact of order collaring policy on large price swings using the GameStop price run-up on January 26th, 2021. In Figure 5, the top plot illustrates the minutely average price path of the GameStop's common stock while the bottom plot depicts dark trades having a *NasdSpd* in (0.25%, 5%).

There are several striking patterns in these plots. First, before the closure of Robinhood, there are frequent dark trades with *NasdSpd* higher than 1%. However, this frequency goes down to almost zero if we consider the period after 6:00 PM during which Robinhood is inactive. Second, we find that excessive positive (negative) spreads are occurring even when the price is decreasing (increasing) implying that the price patterns are not driving these excessive spreads. Third, excessive volatility in GME's price is much higher when Robinhood is open. Before 6:00 PM, there are several episodes of 10% moves in both positive and negative direction. On the other hand, after 6:00 PM, when Robinhood is closed, the stock trades in a much tighter range. Given that there are retail brokerages active after 6:00 PM (e.g., TD Ameritrade, E*Trade), the drop in excessive spreads and price volatility cannot be explained purely by a drop in retail trading. If retail traders are submitting aggressive limit orders with large spreads to the last transaction prices, one would expect to see this in the period after Robinhood's closure. Overall, these plots are consistent with the correlation between excessive price moves and Robinhood's order collaring policy. Note that, in addition to increased retail trading costs, amplified volatility is a significant concern as prices may lose their informativeness for other market participants.

To complement this single-day analysis, we examine GME's after-hours trading patterns more

broadly using data from 2020 to 2021. We compare cumulative daily returns across two periods: 4:00 PM to 6:00 PM when Robinhood is open, and 6:00 PM to 8:00 PM when Robinhood is closed. Figure 6 shows that the price volatility is dramatically higher during Robinhood's trading hours, consistent with our analysis of January 26th. Importantly, we find that the abnormal price surge occurs exclusively during the 4:00 PM to 6:00 PM window, when the average daily return is 37 basis points, accumulating to a striking 311% over the sample period. In contrast, during the 6:00 PM to 8:00 PM window when Robinhood is closed, the average return drops to just 8 basis points, with a cumulative return of only 27%. Given that Robinhood traders are exclusively active in the earlier window, this systematic difference in price surge provides compelling evidence that the order collaring policy may amplify price movements.

7.2. The impact of order collaring on volatility: Evidence from Robinhood closure

Because Robinhood's order collaring policy is active before 6:00 PM, we expect more price volatility before 6:00 PM when compared to the period after 6:00 PM. January 2021 provides an ideal testing sample as retail-heavy stocks experienced extreme volatility due to the meme stock frenzy. To test our hypothesis for all common stocks, we compute the standard deviation of returns in the period before 6:00 PM and after 6:00 PM for each stock on each day in January 2021.

Period 1 (2) will consist of the time interval between 4:00 PM and 6:00 PM (6:00 PM and 8:00 PM). Let $Volatility_{i,t,k}$ be the standard deviation of returns for stock i on day t in period $k \in \{1, 2\}$. Let $TopRetail_{i,t}$ be a binary variable taking the value of 1 if stock i is in the top quintile of percent retail volume on day t (as computed by the BJZZ algorithm). Finally, let $Before6PM_{i,t,k}$ take a value of 1 (0) if $k = 1$ ($k = 2$). We run the following regression to examine the impact of the order collaring policy on the volatility observed before 6:00 PM when Robinhood is open:

$$Volatility_{i,t,k} = \beta_1 TopRetail_{i,t} \times Before6PM_{i,t,k} + \beta_2 TopRetail_{i,t} + \beta_3 Before6PM_{i,t,k} + \sum_j \delta_j ControlVar_{j,i,t,k} + \mu_i + \mu_t + \epsilon_{i,t,k}. \tag{7}$$

We use the logarithm of number of trades, turnover and percent buy volume in each period as control variables and include stock and day fixed effects as denoted by μ_i and μ_t. Standard errors are clustered at the stock-day level.

Table 10 illustrates the regression results. In all specifications, the coefficient on *TopRetail* × *Before6PM* is positive and statistically significant, implying that stocks in the top quintile of percent retail volume on day t experience a relative increase in volatility in the period where order collaring policies are in effect (before 6:00 PM). In reference to the economic magnitude, this result implies that high retail participation stocks experience more than 50 bps increase in return standard deviation due to the collaring policy. Overall, these results raise another concern for regulators, as the order collaring policy–which applies to both share- and dollar-based buy and sell orders in extended hours–potentially amplifies the volatility of transaction prices.

7.3. The impact of order collaring on volatility: Evidence from Robinhood's extension of trading hours

In this section, we extend our difference-in-differences (DiD) experiment to evaluate the impact of Robinhood's after-hours trading extension on volatility. To capture the change in volatility after Robinhood's extension, we again consider the 42-day period before and after the event. These two periods are January 27, 2022 to March 28, 2022 (pre-extension) and March 30, 2022 to May 27, 2022 (post-extension). We use trades occurring between 4:00 PM and 6:00 PM as the control window ($k = 1$) and trades occurring between 6:00 PM and 8:00 PM as the treatment window ($k = 2$).

Again, let $Volatility_{i,t,k}$ be the standard deviation of returns for stock i on day t in period $k \in \{1, 2\}$. Let $After6_{i,t,k}$ take a value of 1 (0) if $k = 2$ ($k = 1$). Finally, let $Post_{i,t,k}$ be equal to 1 if t is later than March 29, 2022, and 0 otherwise. We run the following regression to quantify the impact of Robinhood's after-hours trading extension on the volatility observed:

$$Volatility_{i,t,k} = \beta_1 After6_{i,t,k} \times Post_{i,t,k} + \beta_2 After6_{i,t,k} + \beta_3 Post_{i,t,k} + \sum_j \delta_j ControlVar_{j,i,t,k} + \mu_i + \epsilon_{i,t,k}. \tag{8}$$

We use the logarithm of number of trades, turnover and percent buy volume in each period as control variables and include stock fixed effects. Standard errors are clustered at the stock-day level.

Table 11 illustrates the regression results. In all specifications, the coefficient on *After6* × *Post*

are positive and statistically significant at the 5% level, implying that volatility after 6:00 PM has increased after the extension of the Robinhood's after-hours trading period. The coefficients are also economically significant. On an absolute basis, the increase in return standard deviation is approximately 10 bps. These results further support that stocks are exposed to higher volatility when Robinhood traders employ collared orders in the extended hours period.

8. Conclusion

This paper studies the economics of the default order collaring policy at Robinhood. Since market orders do not have price certainty, Robinhood automatically converts some default orders into limit orders using a 5% spread over prior transaction prices. The stated goal is to protect customer trades from executing at unfavorable prices or extreme spreads. Our analysis instead points to a positive relation between retail execution costs and the order collaring policy.

During regular trading hours, we examine the asymmetric implementation of Robinhood's order-collaring policy and find that buy orders, which are collared, incur an additional trading cost of 3.6 basis points compared to uncollared sell orders on the same stocks. Furthermore, when Robinhood imposed trading restrictions on buy orders, effectively eliminating the use of order collaring for a set of stocks, this additional cost on buy orders largely disappeared.

In after-hours trading, we conduct two quasi-experiments to analyze the effect of order collaring on retail trading costs. First, we take advantage of the collaring policy's discontinuity around the 5% threshold. Second, we examine the extension of trading hours by Robinhood. Before March 29, 2022, Robinhood's after-hours trading session ended at 6:00 PM. After that date, the session was extended to 8:00 PM. In both cases, our analyses reveal that the number of trades occurring at extreme spreads is significantly higher when Robinhood's order-collaring policy is active.

In addition, we examine the presence of extreme volatility due to the presence of the order collaring policy. We use the meme-stock trading period in early 2021 to illustrate how excessive spreads may be playing a role in the formation of extreme price run-ups. Comparing the return volatility before and after 6:00 PM (when the Robinhood closes), we find consistent evidence suggesting that retail trades exposed to order collaring contribute to increased volatility.

we complement these findings with three supporting correlational analyses. First, we demon-

strate a positive correlation between Robintrack popularity metrics and the frequency of costly retail trades. Second, we find a positive correlation between a stock's presence in the "Top Movers" section of the Robinhood app and the number of costly trades. Third, we correlate aggregate retail losses with the popularity of the Robinhood app, as measured by Google search trends over time.

Our paper has important implications with regards to the best execution responsibility of the brokers and how a particular set of retail order handling policies can be harmful to the investor. Moreover, if the order collaring policy is introducing noise into stock prices, then financial markets can become less informative for corporate managers who are responsible for making real investment decisions based on their stock prices (Chen et al., 2007).

References

Ait-Sahalia, Y. and M. Sağlam (2024). High frequency market making: The role of speed. *Journal of Econometrics 239*(2), 105421.

Barber, B. M., X. Huang, P. Jorion, T. Odean, and C. Schwarz (2024). A (sub) penny for your thoughts: Tracking retail investor activity in taq. *The Journal of Finance 79*(4), 2403–2427.

Barber, B. M., X. Huang, T. Odean, and C. Schwarz (2022). Attention-induced trading and returns: Evidence from robinhood users. *The Journal of Finance 77*(6), 3141–3190.

Barber, B. M. and T. Odean (2013). The behavior of individual investors. In *Handbook of the Economics of Finance*, Volume 2, pp. 1533–1570. Elsevier.

Battalio, R., S. A. Corwin, and R. Jennings (2016). Can brokers have it all? On the relation between make-take fees and limit order execution quality. *The Journal of Finance 71*(5), 2193–2238.

Battalio, R., B. Hatch, and M. Sağlam (2024). The cost of exposing large institutional orders to electronic liquidity providers. *Management Science 70*(6), 3597–3618.

Battalio, R. H., R. H. Jennings, M. Saglam, and J. Wu (2023). Identifying market maker trades as' retail'from taq: No shortage of false negatives and false positives. *Available at SSRN 4579159*.

Bessembinder, H., A. Carrion, L. Tuttle, and K. Venkataraman (2016). Liquidity, resiliency and market quality around predictable trades: Theory and evidence. *Journal of Financial Economics 121*(1), 142–166.

Boehmer, E., C. M. Jones, X. Zhang, and X. Zhang (2021). Tracking retail investor activity. *The Journal of Finance 76*(5), 2249–2305.

Chen, Q., I. Goldstein, and W. Jiang (2007). Price informativeness and investment sensitivity to stock price. *The Review of Financial Studies 20*(3), 619–650.

Clark-Joseph, A. D. (2013). Exploratory trading.

Cohn, J. B., Z. Liu, and M. I. Wardlaw (2022). Count (and count-like) data in finance. *Journal of Financial Economics 146*(2), 529–551.

Dyhrberg, A. H., A. Shkilko, and I. M. Werner (2022). The retail execution quality landscape. *Fisher College of Business Working Paper 14*.

Eaton, G. W., T. C. Green, B. S. Roseman, and Y. Wu (2022). Retail trader sophistication and stock market quality: Evidence from brokerage outages. *Journal of Financial Economics 146*(2), 502–528.

Fedyk, V. (2022). This time is different: Investing in the age of robinhood. *Available at SSRN 4112307*.

Hirschey, N. (2021). Do high-frequency traders anticipate buying and selling pressure? *Management Science 67*(6), 3321–3345.

Peress, J. and D. Schmidt (2020). Glued to the tv: Distracted noise traders and stock market liquidity. *The Journal of Finance 75*(2), 1083–1133.

Sağlam, M. (2020). Order anticipation around predictable trades. *Financial Management 49*(1), 33–67.

Welch, I. (2022). The wisdom of the robinhood crowd. *The Journal of Finance 77*(3), 1489–1527.

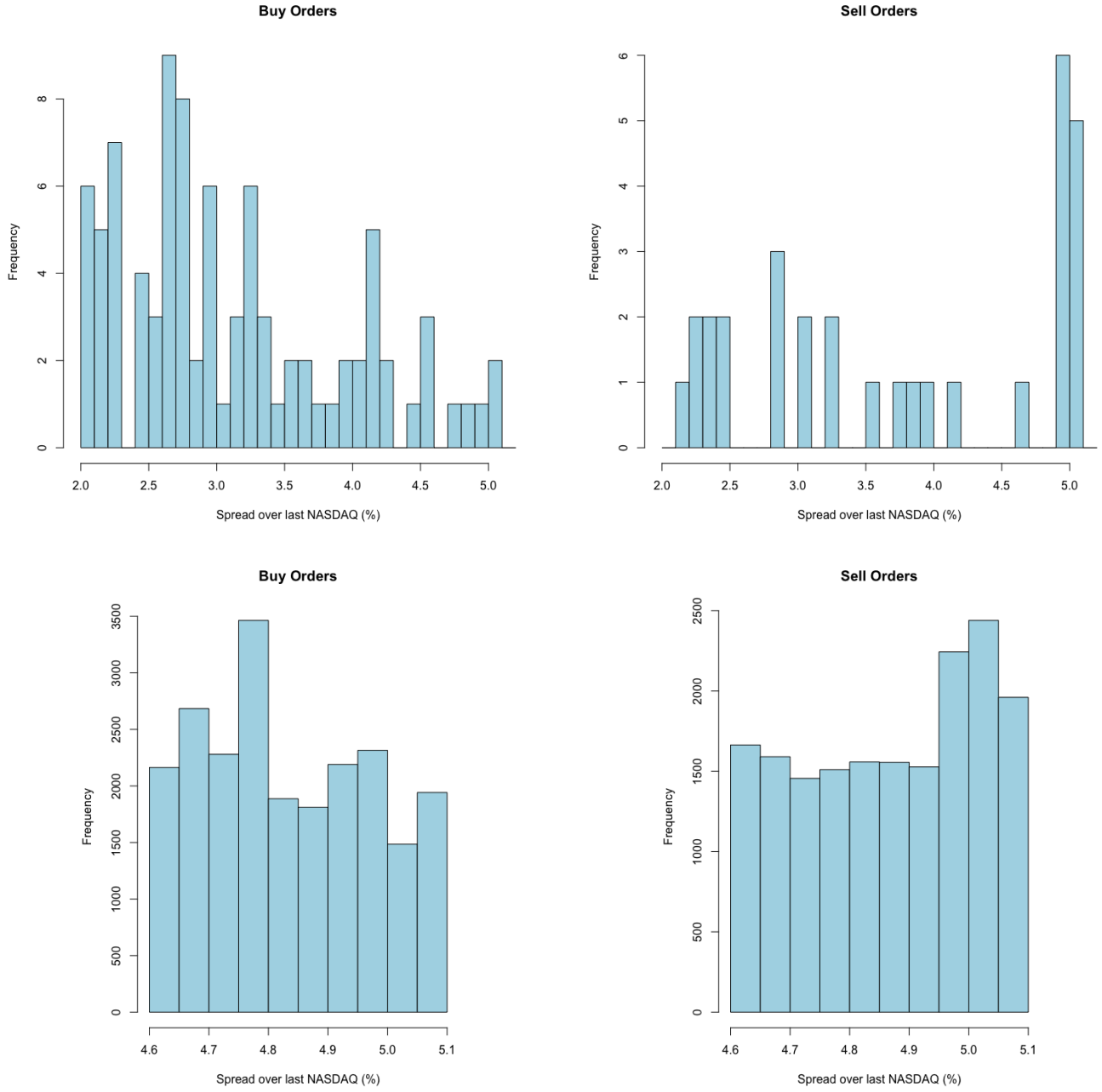


Figure 1: The distribution of the *NasdSpd* of limit buy and sell orders on a retail heavy stock, Virgin Galactic (SPCE) (top panel) and on all stocks (bottom panel).

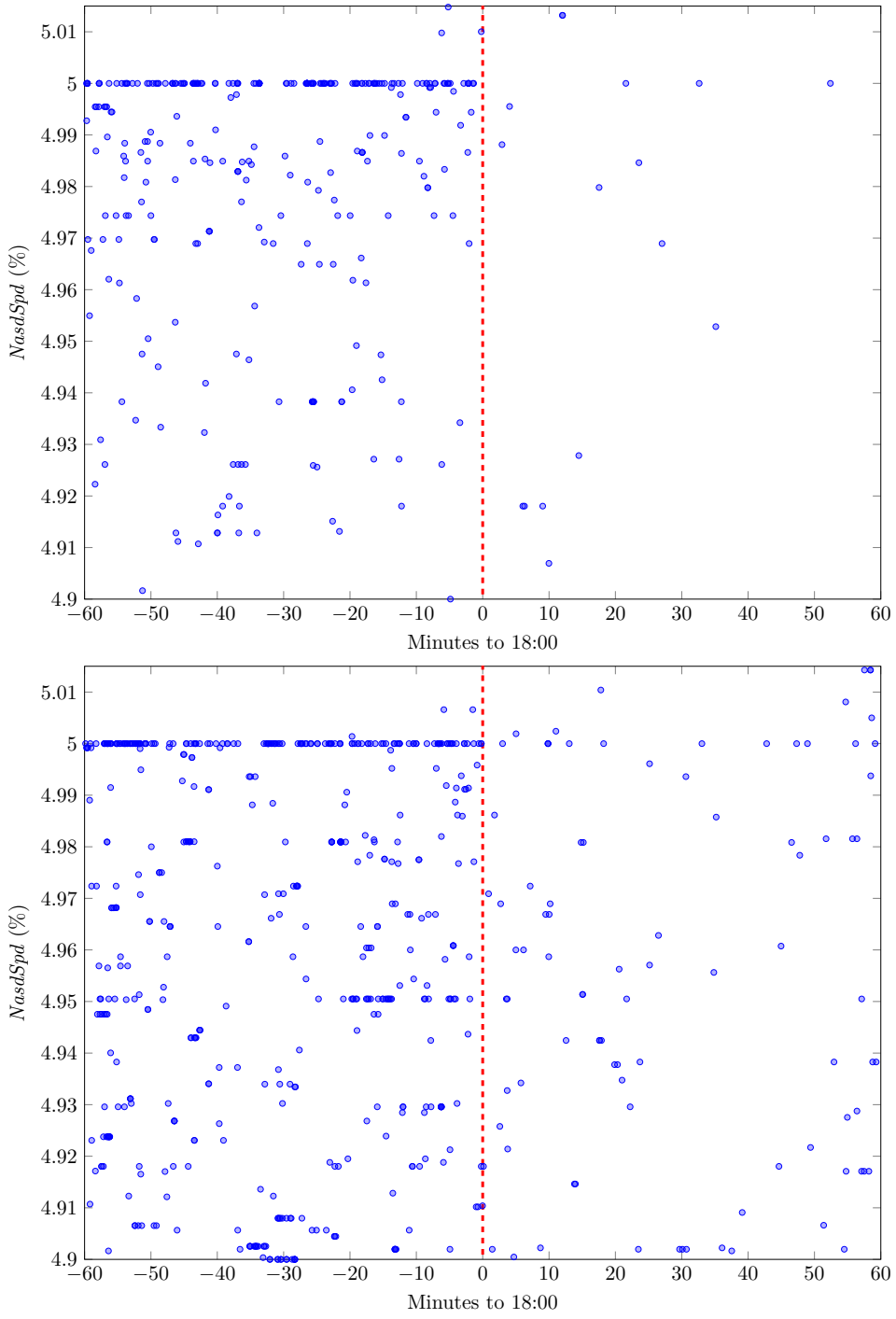


Figure 2: *HNS* trades with a *NasdSpd* of approximately 5% around 18:00 is shown for April 2019 (top panel) and April 2020 (bottom panel). In both periods, Robinhood does not execute orders after 18:00.

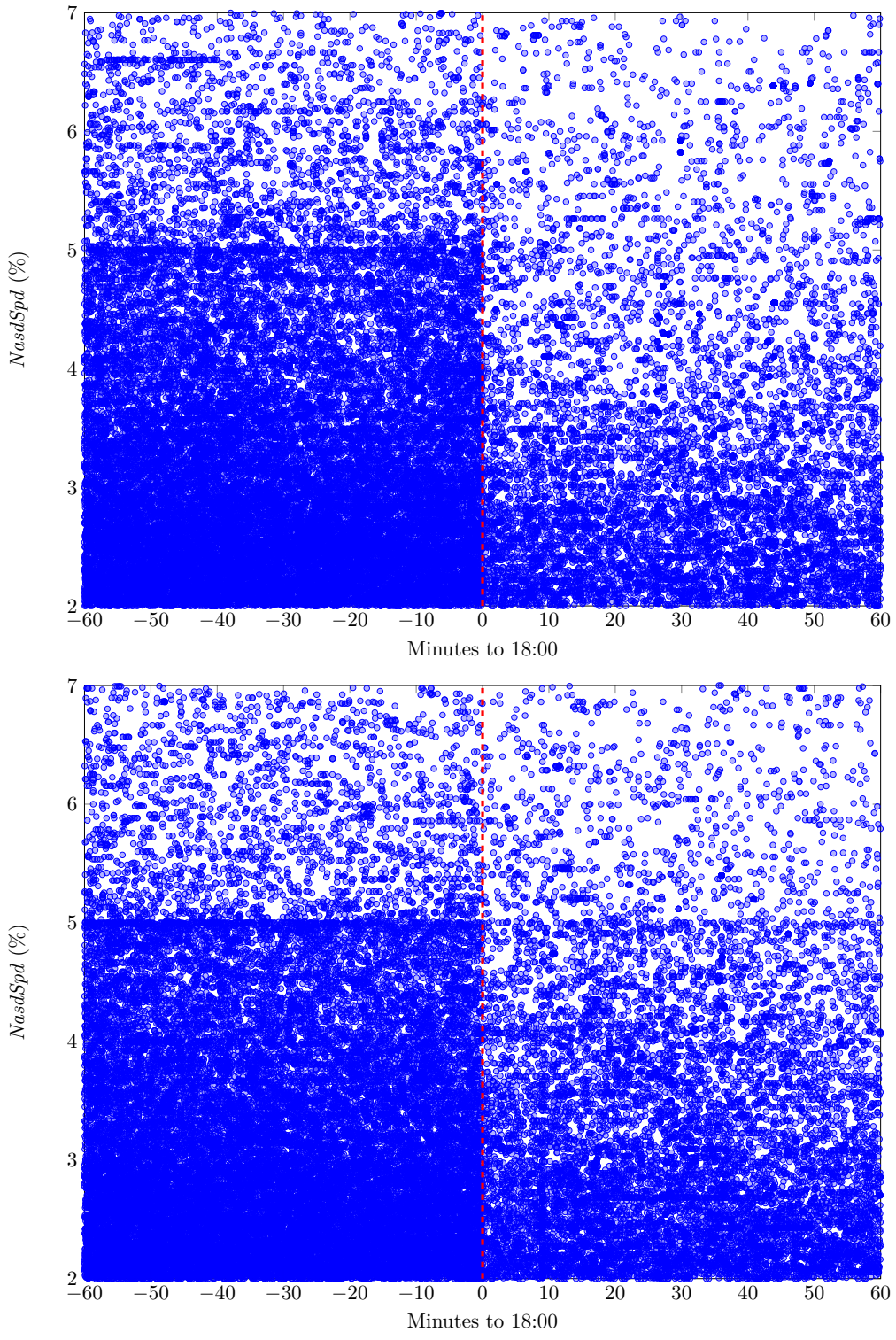


Figure 3: The distribution of after-hours transactions appearing in 'D' exchanges with approximately 5% spread to last NASDAQ trade around 18:00 in March 2022 (top panel) and April 2022 (bottom panel). On March 29, 2022, Robinhood extended its after-hours trading to till 8:00 PM.

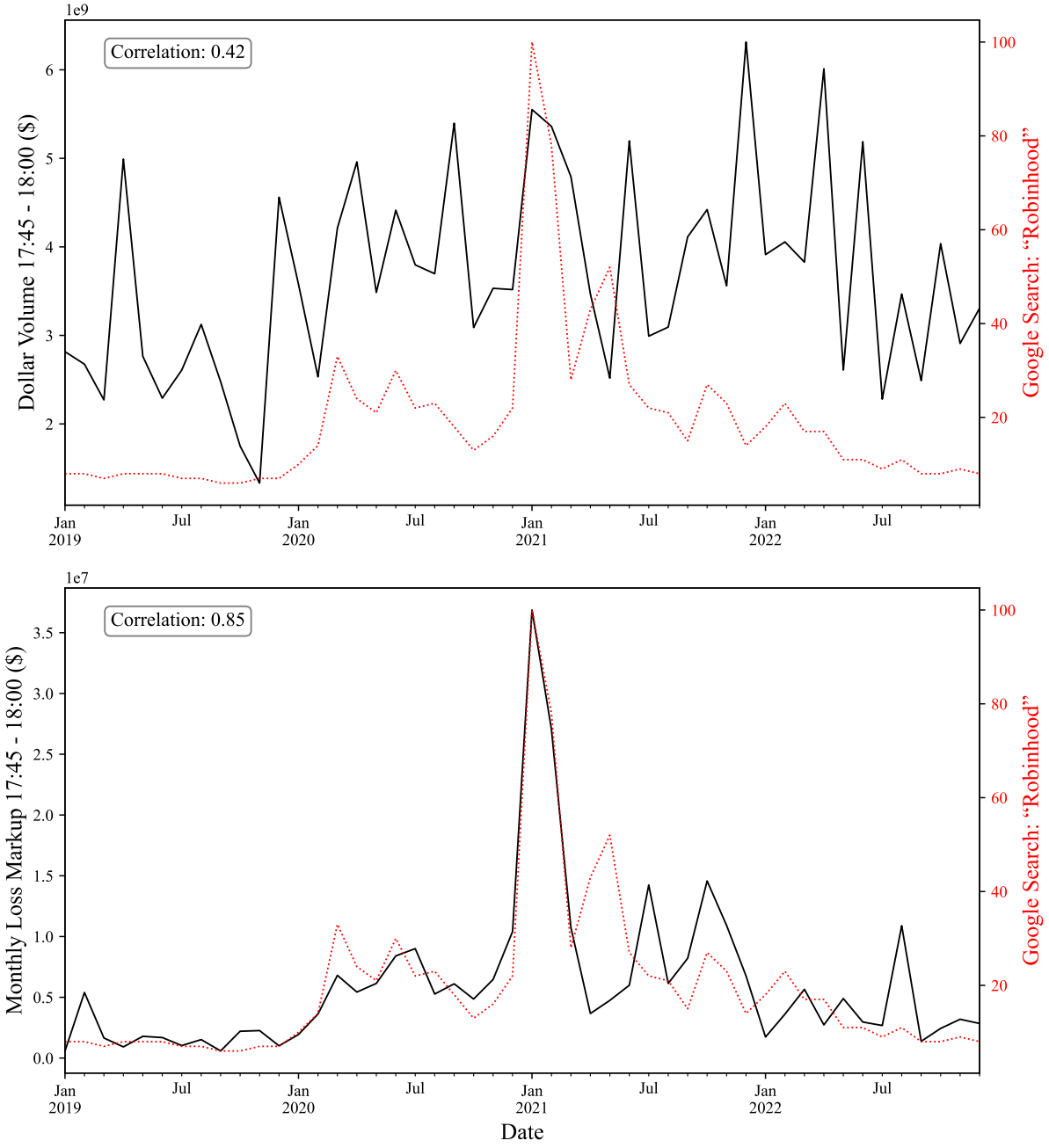


Figure 4: Total dollar volume of the trades occurring between 5:45 PM and 6:00 PM (top panel), the total monthly dollar loss of the HNS trades (when compared to close prices) occurring between 5:45 PM and 6:00 PM (bottom panel) and Google search interest for "Robinhood" between January 2019 and December 2022 (top and bottom panel, red dashed line). Correlation between dollar volume and loss markup compared to search interest can be found in the top left corner of the respective panel. All stocks with share codes 10, 11, 12, 71, and 73 are included.

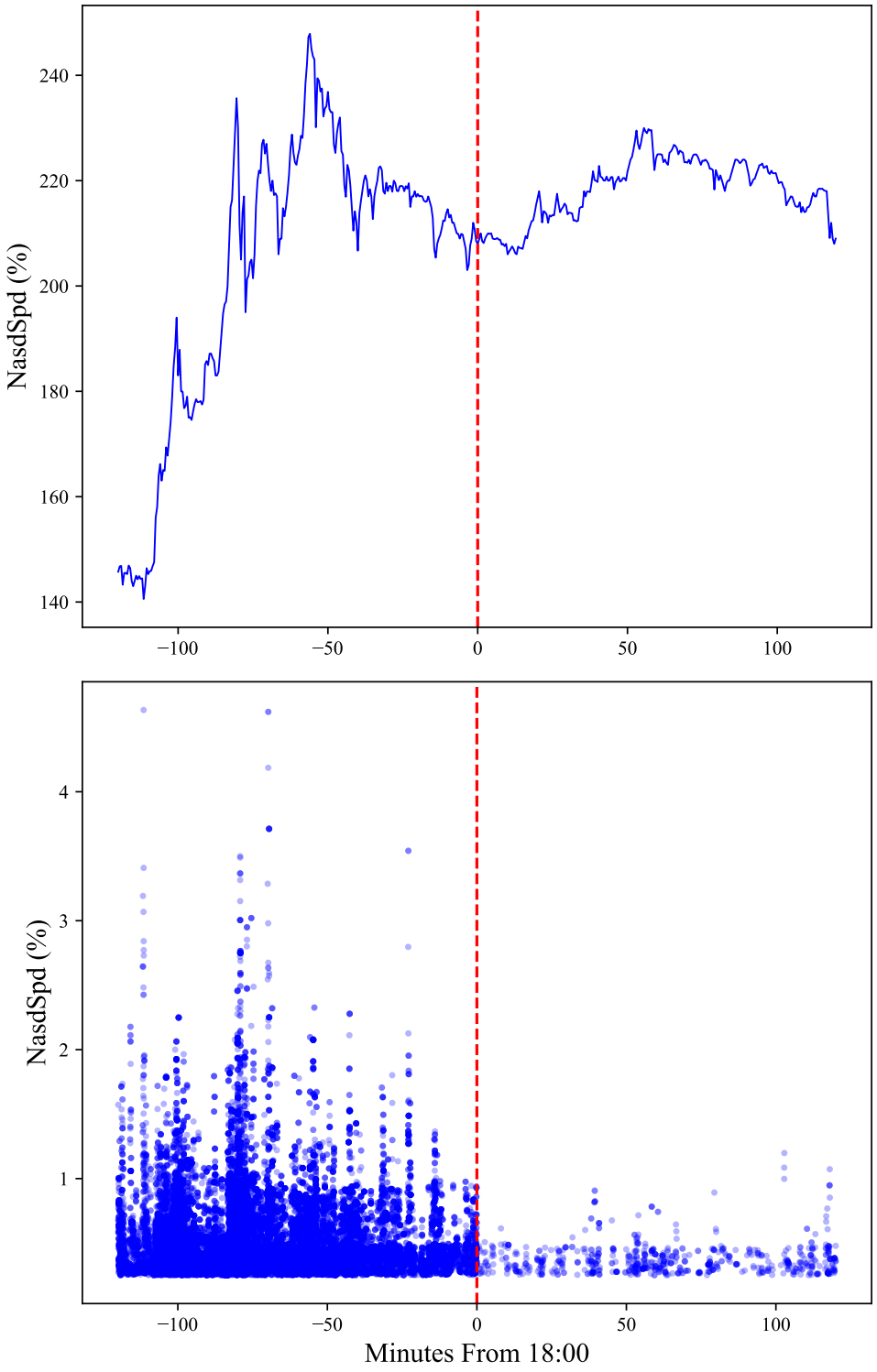


Figure 5: The price path of GME on January 26, 2021 in the after-hours trading period (Top panel). The distribution of after-hours transactions on January 26, 2021 appearing in 'D' exchanges having *NasdSpd* between 0.25% and 5% (Bottom panel). On this day, Robinhood does not allow any trading after 6:00 PM.

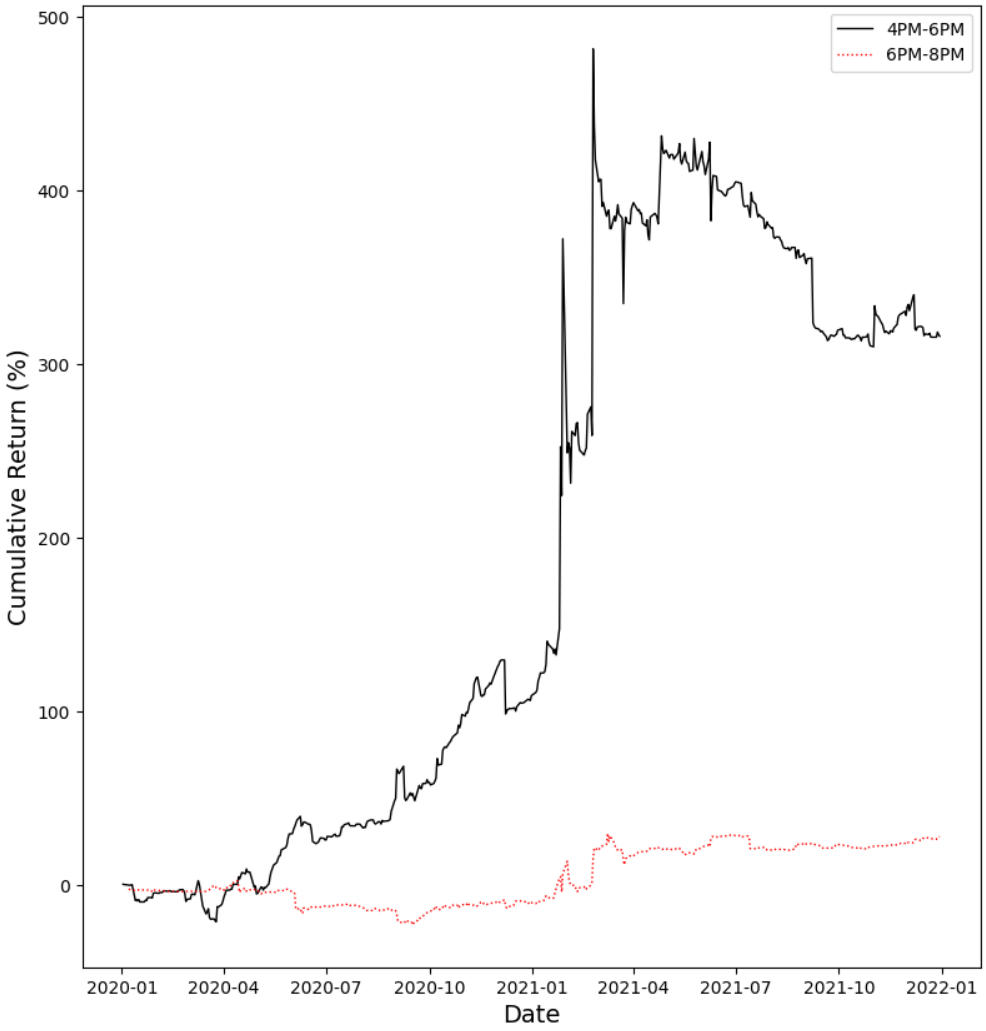


Figure 6: GME cumulative returns during 4:00 PM – 6:00 PM (solid black) and 6:00 PM – 8:00 PM (dashed red) periods.

Table 1: Order types and their exposure to collaring by Robinhood

Notes: This table is created according to the official Robinhood documentation on order types: https://web.archive.org/web/20230123214456/https://robinhood.com/us/en/support/articles/market-order/

Market session	Pre-market	Market hours	After-hours
Before March 29, 2022			
Time Period	9–9:30 AM	9:30 AM–4 PM	4–6 PM
Share-based market buys	✓	✓	✓
Share-based market sells	✓		✓
Dollar-based market buys	✓		✓
Dollar-based market sells	✓		✓
After March 29, 2022			
Time Period	7–9:30 AM	9:30 AM–4 PM	4–8 PM
Share-based market buys	✓	✓	✓
Share-based market sells	✓		✓
Dollar-based market buys	✓		✓
Dollar-based market sells	✓		✓

Table 2: Timeline of Robinhood restrictions in January and February 2021

Notes: This table is created according to figure 39 in the GameStopped report prepared by the majority staff of the committee on financial services, U.S. House of Representatives. https://democrats-financialservices.house.gov/uploadedfiles/6.22_hfsc_gs.report_hmsmeetbp.irm.nlrf.pdf

Date	Daily Restrictions
Thurs Jan 28, 2021	13 stocks on position closing only (PCO) restriction[17]
Fri Jan 29, 2021	50 stocks on account holding / purchase limitations[18]
Mon Feb 1, 2021	8 stocks on account holding / purchase limitations[19]
Tues Feb 2, 2021	5 stocks on account holding / purchase limitations[20]
Weds Feb 3, 2021 Thurs Feb 4, 2021	AMC and GME on account holding / purchase limitations[21]

[17]Position closing only estrictions for 13 stocks, including American Airlines (AAL), AMC Entertainment Holdings (AMC), BlackBerry Ltd. (BB), Bed Bath & Beyond Inc. (BBBY), Castor Maritime Inc. (CTRM), Express, Inc. (EXPR), GameStop (GME), Koss Corp. (KOSS), Naked Brand Group Ltd. (NAKD), Nokia Corp. (NOK), Sundial Growers (SNDL), Tootsie Roll Industries Inc. (TR), and Trivago N.V. (TRVG), announced on Robinhood's website: https://web.archive.org/web/20210128223439/https://robinhood.com/us/en/support/articles/changes-due-to-recent-market-volatility/

[18]Restrictions for 50 stocks on January 29, 2021 announced on Robinhood's website: https://web.archive.org/web/20210130065108/https://robinhood.com/us/en/support/articles/changes-due-to-recent-market-volatility/

[19]Restrictions for 8 stocks on February 1, 2021 announced on Robinhood's website: https://web.archive.org/web/20210201090458/https://robinhood.com/us/en/support/articles/changes-due-to-recent-market-volatility/

[20]Page 73 of GameStopped Report, "During the morning of February 2, 2021, equity position limits remained in place on AMC, EXPR, GME, NAKD, and NOK, but had been lifted on BB, GNUS, and KOSS." https://democrats-financialservices.house.gov/uploadedfiles/6.22_hfsc_gs.report_hmsmeetbp.irm.nlrf.pdf

[21]Restrictions for AMC and GME on February 3rd and 4th, 2021 announced on Robinhood's website: https://web.archive.org/web/20210203130926/https://robinhood.com/us/en/support/articles/changes-due-to-recent-market-volatility/

Table 3: Descriptive statistics of regular trading hours analysis

Notes: This table illustrates the summary statistics of common stocks traded during regular trading hours between April 2020 and December 2020. All stocks included have a close price greater than $1. All trades included have a trade size greater than 1. The *AvgNasdSpdB* and *AvgNasdSpdS* metrics are defined is Section 4.3.

	All Common Stocks April - December 2020			
	Mean	Median	Minimum	Maximum
Close Price	$50.02	$19.40	$1.00	$4,446.88
Market Cap ($B)	$9.632	$0.801	$0.002	$2,299.572
Dollar Volume ($K)	$75,642	$5,738	$0.015	$68,373,673
% Dollar Volume (D Exchange)	36.55%	33.78%	0.00%	100.00%
Number of trades	11,217	3,706	1	2,843,775
% D EX Trades	25.54%	22.17%	0.20%	96.86%
Volume (thousand shares)	1,493	294	0.002	919,998
% D EX Volume	36.55%	33.78%	0.00%	100.00%
Turnover	1.91%	0.56%	0.00%	6901.24%
% Buy	49.01%	49.46%	0.00%	100.00%
% Sell	50.99%	50.54%	0.00%	100.00%
% Buy (D EX)	49.11%	49.39%	0.00%	100.00%
% Sell (D EX)	50.89%	50.61%	0.00%	100.00%
AvgNasdSpdB (bps)	19.98	7.25	-1307.67	2225.56
AvgNasdSpdS (bps)	18.85	7.02	-2026.44	2208.59

Table 4: Descriptive statistics of dark *HNS* trades after market closure.

Notes: This table illustrates the summary statistics of high-NASDAQ-spread (*HNS*) dark trades during after-hours trading period. A trade is classified as *HNS* if it has a *NasdSpd* between 1% and 5%. Lee ready algorithm is used to differentiate buy (*NasdSpdB*) and sell (*NasdSpdS*) trades. *NasdSpd* values for sell trades are multiplied by -1 for ease of comparison between *NasdSpdB* and *NasdSpdS*. In each panel, we compare various statistics of these dark trades between two periods: low retail trading in 2014–2019 and high retail trading in 2020–2022.

Panel A.	**2020–2022**			
	Mean	Median	Minimum	Maximum
Execution Time	5:19:36 PM	4:58:46 PM	4:00:00 PM	8:00:00 PM
Shares Filled	1,258	48	2	20,000,000
Trade Price	$26.71	$5.18	$0.42	$4,884.42
Market Capitalization ($B)	$13.932	$0.377	$0.001	$2,944.128
Number of Trades Per Day	3,323.89	2,820.5	53	22,695
NasdSpdB	1.88%	1.59%	1.00%	5.00%
NasdSpdS	1.85%	1.56%	1.00%	5.00%
	2014–2019			
	Mean	Median	Minimum	Maximum
Execution Time	5:01:09 PM	4:41:40 PM	4:00:00 PM	8:00:00 PM
Shares Filled	5,374	184	2	57,871,731
Trade Price	$33.77	$8.00	$0.25	$4,402.17
Market Capitalization ($B)	$13.809	$0.720	$0.001	$1,270.761
Number of Trades Per Day	378.84	249	1	2,622
NasdSpdB	1.93%	1.63%	1.00%	5.00%
NasdSpdS	1.92%	1.61%	1.00%	5.00%

Panel B.	% of *HNS* Trades			% of *HNS* Trades	
Time Interval	2020–2022	2014–2019	Trade Size Interval	2020–2022	2014–2019
16:00:00 to <16:30:00	25.27%	38.35%	2 - 99	59.47%	39.06%
16:30:00 to <17:00:00	25.43%	23.05%	100 - 499	22.38%	25.04%
17:00:00 to <17:30:00	14.06%	13.71%	500 - 999	6.77%	10.25%
17:30:00 to <18:00:00	12.58%	11.81%	1000 - 1999	5.56%	9.13%
18:00:00 to <18:30:00	5.66%	3.71%	2000 - 4999	3.40%	7.49%
18:30:00 to <19:00:00	5.31%	3.14%	5000 - 9999	1.26%	3.42%
19:00:00 to <19:30:00	4.85%	2.49%	10000+	1.17%	5.61%
19:30:00 to <20:00:00	6.85%	3.75%			

Panel C.	% of *HNS* Trades			% of *HNS* Trades	
Trade Price Interval	2020–2022	2014–2019	Firm Size Interval	2020–2022	2014–2019
>=$1 < $10	65.11%	53.28%	<$50M	15.70%	14.51%
>=$10 < $50	23.71%	28.84%	$50M to < $100M	11.34%	6.00%
>=$50 < $100	4.70%	10.49%	$100M to < $1B	39.99%	35.17%
>=$100 < $250	4.01%	5.38%	$1B to < $100B	30.97%	40.96%
>=$250 < $500	1.33%	1.01%	>$100B	1.99%	3.35%

Table 5: The impact of intraday collaring (April 2020 – December 2020)

Notes: $AvgNasdSpd_{i,t,k}$ is the size weighted mean of *NasdSpd* for all intraday buy and sell dark trades on day t for stock i and $k \in \{b, s\}$. $Buy_{i,t,k}$ is a binary variable taking a value of 1 (0) if k refers to buy (sell) orders. $TopRetail_{i,t}$ is a binary variable taking a value of 1 (0) if i refers to a stock in the top (bottom) quintile of retail volume on day t. AbsDayReturn is the absolute daily return excluding dividends. Turnover is the ratio of the number of shares traded during the trading day to the outstanding number of shares. Daily % Buy is the daily number of buy orders divided by the daily sum of buy and sell orders defined by Lee Ready (1991). LogCloseMktcap is the logarithm of the market capitalization at close. All trades have transaction prices greater than \$1 and trade size greater than 1 share. Each regression includes stock-day level fixed-effects. Standard errors are given in parentheses and are adjusted by double-clustering on stock and day.

	Dependent variable:					
	AvgNasdSpd (bps)					
	(1)	(2)	(3)	(4)	(5)	(6)
Buy × TopRetail	3.60***	3.61***	3.60***	3.62***	3.60***	3.62***
	(0.59)	(0.59)	(0.59)	(0.59)	(0.59)	(0.59)
Buy	−0.11	−0.11	−0.11	−0.10	−0.11	−0.10
	(0.29)	(0.29)	(0.29)	(0.29)	(0.29)	(0.29)
TopRetail	−2.73***	−2.64***	−2.70***	−2.69***	−3.00***	−3.01***
	(0.94)	(0.95)	(0.94)	(0.94)	(0.94)	(0.95)
AbsDayReturn		−6.39***				6.74***
		(1.40)				(2.05)
Turnover			−2.43***			−2.50***
			(0.33)			(0.40)
Daily % Buy				−7.34***		−6.74***
				(1.34)		(1.36)
LogCloseMktcap					−10.81***	−10.59***
					(1.19)	(1.18)
Observations	507,110	506,979	507,110	507,110	507,110	506,979
Adjusted R^2	0.17	0.17	0.17	0.17	0.17	0.17

Table 6: The impact of Robinhood trading restrictions on intraday collaring

Notes: $AvgNasdSpd_{i,t,k}$ is the size weighted mean of *NasdSpd* for all intraday buy and sell dark trades on day t for stock i and $k \in \{b, s\}$. $Buy_{i,t,k}$ is a binary variable taking a value of 1 if k refers to buy orders. $Restricted_{i,t}$ is a binary variable taking a value of 1 (0) if i refers to a stock that has been restricted by Robinhood on day t. AbsDayReturn is the absolute daily return excluding dividends. Turnover is the ratio of the number of shares traded during the trading day to the outstanding number of shares. Daily % Buy is the daily number of buy orders divided by the daily sum of buy and sell orders defined by Lee Ready (1991). LogCloseMktcap is the logarithm of the market capitalization at close. The sample includes common stocks with close a close price greater than \$1 on day t. Further, the sample combines Robinhood restricted stocks on day t and common stocks in the top quintile of percent retail volume. All intraday dark trades in this sample are included from January and February 2021. A timeline of Robinhood restrictions can be found in Table 2. Each regression includes stock-day level fixed-effects. Standard errors are given in parentheses and are adjusted by double-clustering on stock and day.

	Dependent variable:					
	AvgNasdSpd (bps)					
	(1)	(2)	(3)	(4)	(5)	(6)
Buy × Restricted	−3.71***	−3.75***	−3.71***	−3.73***	−3.71***	−3.76***
	(0.75)	(0.75)	(0.75)	(0.75)	(0.75)	(0.74)
Buy	4.84***	4.88***	4.84***	4.86***	4.84***	4.90***
	(0.55)	(0.55)	(0.55)	(0.55)	(0.55)	(0.55)
Restricted	−2.29	−2.02	−2.10	−2.09	1.36	1.13
	(2.06)	(2.04)	(2.07)	(1.99)	(2.99)	(2.91)
AbsDayReturn		−2.48*				4.46***
		(1.35)				(1.03)
Turnover			−1.08***			−1.22***
			(0.24)			(0.24)
Daily % Buy				−11.76***		−11.26**
				(4.38)		(4.41)
LogCloseMktcap					−7.21***	−6.88***
					(1.16)	(1.16)
Observations	57,219	57,206	57,219	57,219	57,219	57,206
Adjusted R^2	0.24	0.24	0.24	0.24	0.24	0.24

Table 7: Regression analysis around the discontinuity at 5% spread

Notes: $NumHCT_{k,t}$ measures the number of high-cost trades in the dark on day t between 4:00 PM and 6:00 PM (across all common stocks) in two spread categories indexed by k. $NumHCT_{0,t}$ is the number of trades in the treatment region where *NasdSpd* is in $[5\% - s, 5\%]$ and s is the bandwidth choice. Similarly, $NumHCT_{1,t}$ is the number of trades in the no-treatment category where *NasdSpd* is in $(5\%, 5\% + s]$. $Treat_{k,t}$ is equal to 1 if k is 0 and 0 otherwise. As control variables, we use Fama-French market return, log of number of trades and log of dollar volume executed after-hours. A Poisson Regression is used and standard errors, clustered by day, are given in parentheses.

Panel A: Actual discontinuity around 5%

	Dependent variable: NumHCT					
	(1)	(2)	(3)	(4)	(5)	(6)
Treat	0.39***	0.34***	0.34***	0.28***	0.40***	0.36***
	(0.07)	(0.10)	(0.05)	(0.06)	(0.07)	(0.09)
LogAHNumTrades	0.58***	0.53*	0.61***	0.7**	0.72***	0.76***
	(0.10)	(0.28)	(0.09)	(0.23)	(0.12)	(0.30)
LogAHDollarVolume	0.21***	0.14*	0.19**	0.13	0.13	0.10
	(0.07)	(0.09)	(0.08)	(0.11)	(0.08)	(0.11)
MktRet	−3.54	−3.61	−1.37	−1.42	1.09	1.45
	(4.64)	(5.03)	(4.50)	(4.80)	(4.42)	(4.85)
Constant	−9.85***	−7.73**	−9.21***	−6.23**	−9.05***	−8.80**
	(1.00)	(3.85)	(1.07)	(3.10)	(1.05)	(3.49)
Bandwidth (%)	0.05	0.05	0.10	0.10	0.15	0.15
Period	All	COVID	All	COVID	All	COVID
Observations	4,518	1,512	4,518	1,512	4,518	1,512
Pseudo R^2	0.31	0.09	0.37	0.09	0.42	0.17

Panel B: Placebo discontinuity around 7%

	Dependent variable: NumHCT					
	(1)	(2)	(3)	(4)	(5)	(6)
Treat	−0.02	−0.14	0.08	0.04	0.07	0.07
	(0.10)	(0.11)	(0.08)	(0.09)	(0.06)	(0.07)
LogAHNumTrades	0.63***	0.50*	0.62***	0.50**	0.65***	0.54***
	(0.10)	(0.26)	(0.09)	(0.21)	(0.08)	(0.19)
LogAHDollarVolume	0.18**	0.21*	0.23***	0.28**	0.18**	0.21**
	(0.09)	(0.11)	(0.09)	(0.12)	(0.08)	(0.10)
MktRet	−5.20	−5.06	−6.59	−6.66	−4.81	−4.49
	(5.44)	(5.56)	(4.38)	(4.43)	(3.83)	(3.94)
Constant	−11.25***	−10.19***	−11.82***	−11.18***	−10.56***	−9.63***
	(1.30)	(3.68)	(1.34)	(3.08)	(1.12)	(2.70)
Bandwidth (%)	0.05	0.05	0.10	0.10	0.25	0.25
Period	All	COVID	All	COVID	All	COVID
Observations	4,518	1,512	4,518	1,512	4,518	1,512
Pseudo R^2	0.21	0.05	0.27	0.08	0.31	0.08

Table 8: Diff-in-Diff analysis around Robinhood's extension of the after-hours trading to 8:00 PM

Notes: $NumHCT_{t,k}$ measure the number of trades with a *NasdSpd* between $5\% - s$ and 5% on day t in the treatment period $k \in \{1, 2\}$ where $k = 1$ ($k = 2$) denotes the trading window between 4:00 PM and 6:00 PM (6:00 PM and 8:00 PM). Finally, let $Post_{t,k}$ be equal to 1 if t is later than March 29, 2022 and 0 otherwise. We use equal number of days for the pre- and post-window by using 42 business days around the effective extension date. As control variables, we use Fama-French market return and log of number of trades and log of dollar volume executed on day t in period k. A Poisson Regression is used and standard errors, clustered by day, are given in parentheses.

	Dependent variable:				
	NumHCT				
	(1)	(2)	(3)	(4)	(5)
After6PM×Post	0.22***	0.40***	0.49***	0.74***	0.99***
	(0.09)	(0.09)	(0.12)	(0.17)	(0.23)
After6PM	−0.66*	−1.10***	−1.20***	−1.43***	−1.25*
	(0.34)	(0.40)	(0.44)	(0.54)	(0.64)
Post	0.12	0.12	0.22*	0.32**	0.18
	(0.09)	(0.10)	(0.11)	(0.14)	(0.16)
LogNumTrades	0.28**	0.18	0.21	0.29	0.25
	(0.13)	(0.16)	(0.19)	(0.21)	(0.25)
LogDollarVolume	−0.04	−0.10	−0.13	−0.18	−0.08
	(0.14)	(0.17)	(0.19)	(0.22)	(0.26)
MktRet	−2.08	−2.14	−1.20	1.35	0.40
	(2.60)	(2.95)	(3.22)	(3.46)	(3.54)
Constant	3.66	5.31*	4.71	3.85	1.19
	(2.53)	(2.96)	(3.25)	(3.91)	(4.81)
Spread Range	[1%,5%]	[2%,5%]	[3%,5%]	[4%,5%]	[4.5%,5%]
Observations	168	168	168	168	168
Pseudo R^2	0.52	0.44	0.35	0.30	0.20

Table 9: The correlation between the number of *HNS* trades and Robinhood order flow

Notes: $Top20Mover_{i,t}$ is an indicator variable taking a value of 1 if stock i is one of the 20 stocks having the largest absolute percentage return between day $t-1$ and t, $TopHeld_{i,t}$ is an indicator variable taking a value of 1 if the stock i is included in the top 5% of all securities with regard to number of accounts holding it on day t and $TopTraded_{i,t}$ is an indicator variable taking a value of 1 if the stock i is included in the top 5% of all securities with regard to sum of absolute changes in the accounts holding it on day t. We use regular-trading-hours turnover, absolute return of the stock, log of closing market capitalization, and after-hours turnover as control variables. A Poisson regression is used with stock and day fixed effects. Standard errors, adjusted by double-clustering on stock and day, are given in parentheses.

	Dependent variable:			
	NumHCTs			
	(1)	(2)	(3)	(4)
Top20Mover	1.59***			1.21***
	(0.08)			(0.07)
TopHold		0.79***		0.04
		(0.16)		(0.15)
TopTraded			1.56***	1.43***
			(0.10)	(0.07)
Turnover	0.24***	0.42***	0.28***	0.16***
	(0.03)	(0.03)	(0.04)	(0.03)
AbsDayReturn	0.40***	0.82***	0.72***	0.38**
	(0.11)	(0.17)	(0.15)	(0.10)
LogCloseMktcap	0.07	0.01	0.00	0.01
	(0.05)	(0.05)	(0.05)	(0.05)
AHTurnover	0.20	0.14	0.15	0.20
	(0.14)	(0.10)	(0.14)	(0.17)
Observations	1,784,620	1,784,620	1,784,620	1,784,620
Pseudo R^2	0.59	0.58	0.60	0.61

Table 10: Volatility before and after 6:00 PM

Notes: $Volatility_{i,t,k}$ measures standard deviation of trade to trade returns for the ith stock on day t in the trading window $k \in \{1, 2\}$. The pseudo-treatment window ($k = 1$) corresponds to trades between 4:00 PM and 6:00 PM, while the pseudo-control window ($k = 2$) corresponds to trades between 6:00 PM and 8:00 PM. Let $TopRetail_{i,t}$ be a binary variable taking the value of 1 if stock i is in the top quintile of percent retail volume on day t. Finally, let $Before6PM_{i,t,k}$ take a value of 1 (0) if $k = 1$ ($k = 2$). We consider all trades in of January 2021. *LogNumTrades* is the logarithm of number of trades executed for stock i during period k on day t. *Turnover* is the ratio of the number of shares traded for stock i during period k on day t to the outstanding number of shares. *% Buy* is buy volume divided by total volume transacted for stock i during period k on day t. All trades have transaction prices greater than \$1. Each regression includes stock and day level fixed-effects. Standard errors are given in parentheses and are adjusted by double-clustering on stock and day.

	Dependent variable:				
	Volatility (bps)				
	(1)	(2)	(3)	(4)	(5)
Before6PM×TopRetail	53.36***	50.71***	53.47***	53.36***	50.80***
	(7.53)	(7.41)	(7.53)	(7.52)	(7.40)
Before6PM	−60.49***	−55.14***	−60.45***	−60.49***	−55.26***
	(7.32)	(7.32)	(7.32)	(7.31)	(7.31)
TopRetail	−47.38***	−44.47***	−47.47***	−47.38***	−44.55***
	(7.79)	(7.69)	(7.78)	(7.76)	(7.65)
LogNumTrades		−3.26***			−3.18***
		(1.01)			(1.05)
Turnover			−51.54**		−11.79
			(20.26)		(13.07)
% Buy				0.10	0.31
				(1.71)	(1.74)
Observations	32,043	32,043	32,043	32,043	32,043
Adjusted R^2	0.38	0.38	0.38	0.38	0.38

Table 11: Volatility after 6:00 PM when Robinhood is open

Notes: $Volatility_{i,t,k}$ measures standard deviation of trade to trade returns for the ith stock on day t in the trading window $k \in \{1, 2\}$. The control window ($k = 1$) corresponds to trades between 4:00 PM and 6:00 PM, while the treatment window ($k = 2$) corresponds to trades between 6:00 PM and 8:00 PM. Let $After6_{i,t,k}$ take a value of 1 (0) if $k = 2$ ($k = 1$). Finally, let $Post_{i,t,k}$ be equal to 1 if t is later than March 29, 2022, and 0 otherwise. We consider two periods: January 27, 2022 to March 28, 2022 (42 days pre-extension), and March 29, 2022 to May 26, 2022 (42 days post-extension). *LogNumTrades* is the logarithm of number of trades executed for stock i during period k on day t. *Turnover* is the ratio of the number of shares traded for stock i during period k on day t to the outstanding number of shares. *% Buy* is buy volume divided by total volume transacted for stock i during period k on day t. All trades have transaction prices greater than \$1. Each regression includes stock level fixed-effects. Standard errors are given in parentheses and are adjusted by double-clustering on stock and day.

	Dependent variable:				
	Volatility (bps)				
	(1)	(2)	(3)	(4)	(5)
After6PM×Post	10.80***	10.96***	10.76***	11.04***	11.18***
	(2.82)	(2.91)	(2.82)	(2.83)	(2.92)
After6PM	9.65***	−2.57	9.52***	9.81***	−2.29
	(1.85)	(2.35)	(1.85)	(1.85)	(2.35)
Post	16.67***	17.11***	16.69***	16.48***	16.93***
	(2.26)	(2.33)	(2.26)	(2.25)	(2.32)
LogNumTrades		−10.71***			−10.56***
		(0.84)			(0.85)
Turnover			−296.91***		−105.55***
			(70.50)		(28.34)
% Buy				−5.00***	−4.81***
				(0.73)	(0.75)
Observations	329,992	329,992	329,992	329,992	329,992
Adjusted R^2	0.24	0.25	0.24	0.24	0.25

Online Appendix

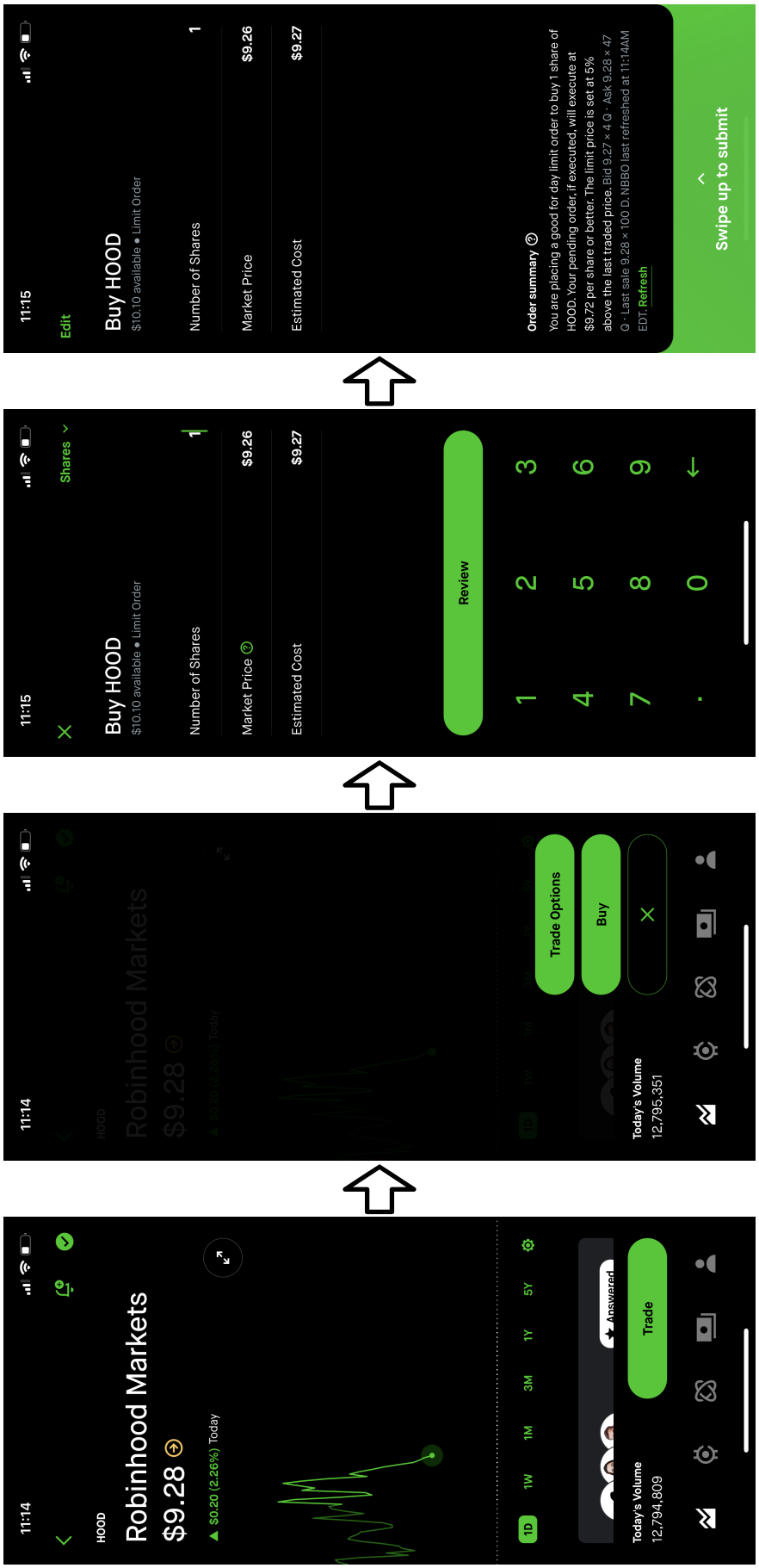


Figure A.1: The user-interface flow for submitting share-based orders on Robinhood mobile trading platform.



Figure A.2: The user-interface flow for submitting a standard limit order on Robinhood mobile trading platform.

Table A.1: Snapshot of after-hours trading in AMC Entertainment on January 27th, 2021

Notes: This table illustrates a snapshot of after-hours trading in AMC Entertainment on January 27th, 2021. In the table you can see that 'D' exchange trades are trading at more than 4% premium compared to trades executing on other exchanges ('P', 'T', and 'K').

Date	Time	Symbol	Exchange	Size	Price
2021-01-27	4:00:00 PM	AMC	Close Price		$ 19.90
2021-01-27	4:31:39 PM	AMC	D	15	$ 16.50
2021-01-27	4:31:39 PM	AMC	D	15	$ 16.59
2021-01-27	4:31:39 PM	AMC	T	1	$ 15.84
2021-01-27	4:31:39 PM	AMC	P	69	$ 15.80
2021-01-27	4:31:39 PM	AMC	D	100	$ 16.59
2021-01-27	4:31:39 PM	AMC	P	45	$ 15.83
2021-01-27	4:31:39 PM	AMC	D	50	$ 16.59
2021-01-27	4:31:39 PM	AMC	D	50	$ 16.50
2021-01-27	4:31:39 PM	AMC	D	50	$ 16.59
2021-01-27	4:31:39 PM	AMC	D	7	$ 16.59
2021-01-27	4:31:39 PM	AMC	D	7	$ 16.50
2021-01-27	4:31:39 PM	AMC	D	7	$ 16.59
2021-01-27	4:31:39 PM	AMC	T	157	$ 15.84
2021-01-27	4:31:39 PM	AMC	T	100	$ 15.84
2021-01-27	4:31:39 PM	AMC	P	1	$ 15.83
2021-01-27	4:31:39 PM	AMC	P	43	$ 15.85
2021-01-27	4:31:39 PM	AMC	K	200	$ 15.85
2021-01-27	4:31:39 PM	AMC	T	300	$ 15.85
2021-01-27	4:31:39 PM	AMC	D	5	$ 16.63
2021-01-27	4:31:39 PM	AMC	D	5	$ 16.50

Table A.2: The impact of intraday collaring using SEC rule 605 data (April 2020 – December 2020)

Notes: $AvgNasdSpd_{i,t,k}$ is the size weighted mean of *NasdSpd* for all intraday buy and sell dark trades on day t for stock i and $k \in \{b, s\}$. $Buy_{i,t,k}$ is a binary variable taking a value of 1 (0) if k refers to buy (sell) orders. $TopRetail_{i,t}$ is a binary variable taking a value of 1 (0) if i refers to a stock in the top (bottom) quintile of retail volume for day t in month m as defined by SEC rule 605 data. AbsDayReturn is the absolute daily return excluding dividends. Turnover is the ratio of the number of shares traded during the trading day to the outstanding number of shares. Daily % Buy is the daily number of buy orders divided by the daily sum of buy and sell orders defined by Lee Ready (1991). LogCloseMktcap is the logarithm of the market capitalization at close. All trades have transaction prices greater than \$1 and trade size greater than 1 share. Each regression includes stock-day level fixed-effects. Standard errors are given in parentheses and are adjusted by double-clustering on stock and day.

	Dependent variable:					
	AvgNasdSpd (bps)					
	(1)	(2)	(3)	(4)	(5)	(6)
Buy × TopRetail	3.84***	3.85***	3.84***	3.85***	3.84***	3.85***
	(0.75)	(0.75)	(0.75)	(0.75)	(0.75)	(0.75)
Buy	−0.33**	−0.33**	−0.33**	−0.32*	−0.33**	−0.32*
	(0.17)	(0.16)	(0.17)	(0.16)	(0.17)	(0.16)
TopRetail	−5.07	−4.87	−4.89	−4.80	−5.45	−5.25
	(3.92)	(3.94)	(3.92)	(3.92)	(3.93)	(3.94)
AbsDayReturn		−7.00***				5.33**
		(1.28)				(2.18)
Turnover			−2.51***			−2.43***
			(0.31)			(0.38)
Daily % Buy				−5.42***		−4.42***
				(1.41)		(1.43)
LogCloseMktcap					−12.42***	−12.21***
					(1.22)	(1.21)
Observations	503,690	503,541	503,690	503,690	503,690	503,541
Adjusted R^2	0.19	0.19	0.19	0.19	0.19	0.19

Table A.3: The impact of intraday collaring (January 2019 – November 2019)

Notes: $AvgNasdSpd_{i,t,k}$ is the size weighted mean of *NasdSpd* for all intraday buy and sell dark trades on day t for stock i and $k \in \{b, s\}$. $Buy_{i,t,k}$ is a binary variable taking a value of 1 (0) if k refers to buy (sell) orders. $TopRetail_{i,t}$ is a binary variable taking a value of 1 (0) if i refers to a stock in the top (bottom) quintile of retail volume on day t. AbsDayReturn is the absolute daily return excluding dividends. Turnover is the ratio of the number of shares traded during the trading day to the outstanding number of shares. Daily % Buy is the daily number of buy orders divided by the daily sum of buy and sell orders defined by Lee-Ready. LogCloseMktcap is the logarithm of the market capitalization at close. All trades have transaction prices greater than \$1 and trade size greater than 1 share. Each regression includes stock-day level fixed-effects. Standard errors are given in parentheses and are adjusted by double-clustering on stock and day.

	Dependent variable:					
	AvgNasdSpd (bps)					
	(1)	(2)	(3)	(4)	(5)	(6)
Buy × TopRetail	3.05***	3.08***	3.05***	3.09***	3.05***	3.12***
	(0.64)	(0.64)	(0.64)	(0.64)	(0.64)	(0.64)
Buy	−1.10***	−1.12***	−1.10***	−1.08***	−1.10***	−1.11***
	(0.25)	(0.25)	(0.25)	(0.25)	(0.25)	(0.25)
TopRetail	−4.65***	−4.76***	−4.65***	−4.72***	−5.38***	−5.58***
	(0.72)	(0.73)	(0.72)	(0.72)	(0.72)	(0.73)
AbsDayReturn		15.76***				18.00***
		(5.25)				(5.44)
Turnover			−0.03**			−0.09***
			(0.01)			(0.02)
Daily % Buy				−7.97***		−7.63***
				(1.26)		(1.25)
LogCloseMktcap					−13.41***	−13.37***
					(1.32)	(1.30)
Observations	587,171	587,100	587,171	587,171	587,171	587,100
Adjusted R^2	0.16	0.16	0.16	0.16	0.16	0.16