Zero-Commission Individual Investors, High Frequency Traders, and Stock Market Quality

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Abstract

We find that Robinhood ownership changes are unrelated with future returns, suggesting that zero-commission investors behave as noise traders. We exploit Robinhood platform outages to identify the causal effects of commission-free traders on financial markets. Exogenous negative shocks to Robinhood participation are associated with increased market liquidity and lower return volatility among stocks favored by Robinhood investors, as proxied by Reddit WallStreetBets mentions. HFTs with Robinhood order flow arrangements quote narrower lit-market spreads during outages, and market depth order imbalances fall, particularly for stocks with highly autocorrelated order flow, suggesting that zero-commission investors create liquidity-reducing inventory risks for market makers.

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1. Introduction

The recent arrival of investing platforms with zero trading commissions and no account minimums has ushered in a new era of stock market participation. Robinhood reported 3 million new accounts in the first quarter of 2020 alone, as the pandemic shutdown put many other activities on hold, and retail investors now routinely account for roughly 20% of stock market activity (Fitzgerald, 2020; Winck, 2020). In this article, we study breadth of ownership data from Robinhood to explore the financial market implications of commission-free individual investors.

Investors drawn to zero commissions and user-friendly trading platforms tend to be younger and less wealthy than retail investors from previous decades.[1] Consistent with lack of expertise, we find no evidence that changes in Robinhood ownership predict future returns. This contrasts with evidence from other studies that broader measures of retail order flow positively predict stock returns (Kaniel, Saar, and Titman, 2008; Kaniel, et al., 2012; Kelley and Tetlock, 2013, 2017; Barrot, Kaniel, and Sraer, 2016; Boehmer, et al., 2020; Farrell, et al., 2020). Robinhood investors' evident lack of skill in aggregate is consistent with commission-free investors behaving as uninformed noise traders.[2]

An influx of noise traders could potentially enhance or harm stock market liquidity. In canonical adverse selection microstructure models such as Glosten and Milgrom (1985) and Kyle (1985), an increase in noise trading reduces the likelihood that market makers face informed traders, which should lead to improved market liquidity. On the other hand, inventory risk models

[1] For example, Robinhood's mean investor is 31 years old with average account balances between $1000 and $5000 (Venkateswaran, 2019), compared with 50 years old and $47,000 in the heavily studied US retail brokerage sample from the 1990s (e.g. Barber and Odean, 2001). Moreover, Robinhood investors appear to have modest experience levels as our analysis of website traffic reveals that the most popular Robinhood FAQ topic is "what is the stock market."

[2] Many retail-oriented brokerages have followed Robinhood and reduced their trading commissions to zero. As a result, "zero-commission" technically applies to most retail investors. We use the term "zero-commission" to describe younger, less wealthy, and less experienced investors drawn to zero commissions, no account minimums, and easy-to-use interfaces.

such as Ho and Stoll (1981) and Grossman and Miller (1988) emphasize that market makers are concerned about fluctuations in their inventory's value, which may be magnified by noise trading shocks. In this setting, an increase in noise trading may result in reduced liquidity.

Zero-commission investors' effect on market liquidity is likely mediated by high frequency traders (HFTs). The economics of commission-free trading depend on payment for order flow arrangements, in which liquidity-providing HFTs pay retail brokers a fee for the opportunity to act as market maker on their orders off-exchange. Academic studies typically support the view that HFTs produce lower bid-ask spreads and improved price efficiency (e.g. Hendershott, Jones, and Menkveld, 2011; Brogaard, Hendershott, and Riordan, 2015), and it is possible that observing uninformed order flow allows HFTs to more effectively provide liquidity. On the other hand, other studies document a positive relation between HFT activity and short-term volatility (e.g. Kirilenko, et al, 2017; Shkilko and Sokolov, 2020), and suggest that HFTs engage in predatory trading (van Kervel and Menkveld, 2019; Hirschey, 2020). If zero commission investors' trading behavior, such as herding, is predictive of future price changes (e.g. Barber, et al., 2020), HFTs may observe retail order flow and become informed in a way that increases adverse selection for other market makers.

Identifying the effect of retail investor trading on stock market quality is challenging because trading activity is endogenous. Foucault, Sraer, and Thesmar (2011) rely on a French legal reform that discouraged retail trading and find evidence that stock market liquidity improved following the regulation change. On the other hand, Peress and Schmidt (2020) find evidence that reduced noise trading is associated with lower stock market liquidity using distracting US news stories to proxy for low attention from noise traders. Our approach for isolating the effects of zero-commission investors on market quality relies on trading platform outages. Robinhood has experienced periodic infrastructure instability (e.g. Smith, 2020). Although lengthy delays are rare, DownDetector.com, a web platform that compiles user complaints, lists events on 25 separate trading days during our eight-month sample period in which at least 200 Robinhood users report outages. The median length of the outages in the sample is 30 minutes.

Analyzing the market effects of Robinhood platform outages requires a forecast of which stocks Robinhood investors would have traded in the absence of the outage. Our main proxy relies on message board activity from the Reddit WallStreetBets forum (r/wallstreetbets), which has "become synonymous with retail zeal in the pandemic age" (Kochkodin, 2021).[3] We also consider a measure of lagged Robinhood trading activity to proxy for expected trading during outages. We confirm that mentions on WallStreetBets as well as lagged ownership changes strongly predict future changes in Robinhood ownership in general, and we explore the effects of platform outages on stocks with high expected Robinhood trading.

Our empirical approach compares market quality during Robinhood platform outages to similar times of day over the previous week. In particular, we use indicator variables to contrast the effects of outages on stocks with high expected Robinhood trading ("Robinhood stocks") relative to other stocks. The difference-in-differences type approach helps mitigate concerns that outages may be related to market-wide news. We also conduct several analyses to address concerns that outages may be endogenous.[4]

We begin by validating that Robinhood platform outages are associated with reduced trading activity. We find that stocks favored by Robinhood investors experience significantly

[3] Supporting the relevance of platform outages, we note that mentions of the word "Robinhood" increase significantly on WallStreetBets during Downdetector reported outages.

[4] We compare the impact of outages with pseudo non-events assumed to take place one hour after the reported outage. We also consider specifications in which we exclude stocks with large increases in WallStreetBets mentions on the day of the outage, which helps address concerns that individual firm news may drive outages. Moreover, for the subset of 15-minute outages, we plot outcome variables before, during, and after the outage.

lower trading intensity and volume during platform outages. For example, using WallStreetBets mentions as the proxy for Robinhood-favored stocks, and controlling for firm and day fixed effects, we find outages are associated with 6.2% fewer trades. We observe no differences for the placebo pseudo-outages measured one-hour after the event.

We analyze several measures of market quality: quoted spreads, effective spreads, realized spreads, and price impact. For each liquidity measure, we find robust evidence that Robinhood platform outages are associated with improved market quality among stocks favored by Robinhood investors, with no differences for the pseudo-outages. For example, using the WallStreetBets proxy for Robinhood stocks, we find that outages are associated with price impacts that are 5.1 basis points lower, relative to a mean of 61 basis points. The implication is that the presence of zero-commission investors is harmful to market liquidity.

Robinhood outages are also associated with lower return volatility. Specifically, we calculate volatility using transaction price changes during five-minute windows, and we find that volatility is significantly lower among Robinhood stocks during platform outages. For example, using WallStreetBets mentions as the proxy for Robinhood-favored stocks, outages are associated with 17 basis point lower transaction price volatility, meaningful relative to the mean of 240 basis points. The outage evidence suggests that zero-commission traders contribute to volatility, in line with noise trading models such as DeLong et al. (1990), Campbell and Kyle (1993), and Llorente et al. (2002).

The evidence that Robinhood outages are associated with improved market quality raises the natural question of how off-exchange (dark) trading influences measures of public market (lit) quality. In recent times, the HFT firms that act as wholesalers by internalizing retail orders off exchange are also among the largest market makers in public markets, which suggests that zero-commission trading likely influences lit market quality through these HFT algorithms.[5] Supporting this view, we find evidence consistent with greater liquidity provision during Robinhood outages specifically by HFTs with payment for order flow arrangements with Robinhood. In particular, we examine non-anonymous dealer quotes available on public markets, and we find that outages are associated with significantly narrower dealer spreads for Robinhood-affiliated HFTs (e.g. Citadel Securities and Virtu Financial), and no significant change for other dealer quotes.

The intuition behind payment for order flow arrangements holds that HFTs face lower informed trader risk when engaging with retail investors, which allows for liquidity provision at better rates than available on public markets. On the other hand, if zero-commission investors herd in ways that leads to autocorrelated trading, this can introduce inventory risk that hinders HFTs ability to provide liquidity. We explore the inventory risk channel in two ways. First, we examine whether market depth becomes more balanced during Robinhood outages. Consistent with reduced inventory imbalances, we find that outages coincide with lower market depth imbalances overall, and Robinhood-affiliated dealer quotes are more likely to be centered around the prevailing midquote. Autocorrelated trading makes it more difficult for market makers to unload inventory, and in our final analysis we proxy for inventory risk with the strength of autocorrelation in Robinhood trading. Using triple-interaction terms, we find that the positive effects of Robinhood outages on market quality are the strongest for stocks with high order flow autocorrelation.

Taken together, the findings support the view that zero-commission traders have negative effects on stock market quality, consistent with behavioral noise trader and inventory risk models.

[5] For example, two of the three designated market maker firms on NYSE (Citadel Securities and Virtu Financial) also internalize orders for Robinhood. FINRA regulation 5320, which prohibits front-running of customer orders, requires that HFT firms implement information barriers between trading units so that one unit (e.g., the market making division) does not obtain knowledge of customer orders from another unit (e.g., the wholesale division). However, the algorithms for both units will be influenced by the firm's overall position and internal risk tolerance.

The Robinhood platform outage results are consistent with the French legal reform evidence in Foucault, Sraer, and Thesmar (2011), but contrast with the distracting US news story evidence in Peress and Schmidt (2020). We note that the sample in Peress and Schmidt (2020) ends in 2014, and one plausible explanation for the difference is that the arrival of zero-commission brokers (along with no account minimums and easy-to-use platforms) has attracted a new type of uninformed equity market participant that in aggregate has a negative impact on market quality.

Our analysis contributes to several strands of literature. First, we add to the literature on retail investing skill. Recent research suggests that retail trades in aggregate positively predict future returns and earnings surprises (Kaniel et al., 2008; 2012; Kelley and Tetlock 2013; Barrot, Kaniel, and Sraer, 2016; Boehmer et al., 2020). In contrast, we document that firm-level changes in Robinhood ownership are at best unrelated to future returns, consistent with uninformed trading documented in early studies of retail investors (e.g. Barber and Odean, 2000).

In addition, our research adds to the literature that examines the effects of financial social media on financial markets. Several studies find evidence that certain types of social media can provide investment value (Chen, et al., 2014; Jame, et al., 2016; Farrell, et al., 2020), whereas other work suggests that social media may spread stale news or intensify behavioral biases (Heimer, 2016; Cookson, Engelberg, and Mullins, 2020). Cookson, Fos, and Niessner (2021) measure retail investor disagreement using StockTwits, and they find that disagreement is associated with greater liquidity that facilitates trading by activist investors. We find that the Reddit WallStreetBets forum, which is often comprised of brief posts, nevertheless strongly predicts future zero-commission retail trading in ways that have implications for market quality.[6]

[6] Pedersen (2021) models beliefs in a setting where investors learn via social networks and highlights how fake news can lead to bursts of high volume and excess volatility.

We also shed light on the effects of high frequency traders on financial markets. Empirical evidence is mixed regarding whether HFT activity improves market quality (e.g. Hendershott, Jones, and Menkveld, 2011; Brogaard, Hendershott, and Riordan, 2015), or detracts from it (e.g. Kirilenko, et al, 2017; Shkilko and Sokolov, 2020). In particular, van Kervel and Menkveld (2019) find evidence that HFTs engage in predatory trading around large institutional orders, whereas Korajczyk and Murphy (2019) argue that HFTs are associated with lower transaction costs for small, uninformed trades. We find evidence that Robinhood-affiliated HFTs exhibit smaller inventory imbalances and provide greater liquidity during outages, in line with inventory risk interpretations and inconsistent with HFTs trading in predatory ways on zero-commission order flow. Our findings also connect with the literature on off-exchange trading (e.g. Menkveld, Yueshen, and Zhu, 2017; Buti, Rindi, and Werner, 2017) and payment for order flow (e.g. Easley et al., 1996; Battalio, 1997; Bessembinder and Kaufman, 1997; Comerton-Forde, Malinova, and Park, 2018), which examines how payment for order flow influences adverse selection across trading venues. Our evidence suggests that uninformed order flow executed off exchange can introduce inventory risk that influences liquidity provision on public markets.

Our work is related to contemporaneous studies of Robinhood investors. Welch (2020) notes that Robinhood investors purchased in aggregate during the pandemic downturn, but also added funds aggressively after large upswings, generally consistent with uninformed trading. Illustrating that Robinhood investors can influence market conditions, Barber, et al. (2020) finds that attention-induced herding by Robinhood investors is accompanied by large price movements and subsequent reversals. Glossner et al. (2020) highlight that Robinhood investors tended to purchase stocks during the pandemic that institutions sold, consistent with liquidity provision.[7]

[7] We note that our findings are robust if we exclude March 2020, which exhibited the steepest market drops of the pandemic.

Ozik, Sadka, and Shen (2020) also study the effects of Robinhood investors on market liquidity and address causality by relying on investor home bias and using the staggered implementation of stay-at-home advisories during the pandemic. They argue that Robinhood investors alleviate illiquidity, although they acknowledge that the evidence is weaker among high-media-attention stocks that are frequently traded by Robinhood investors. Our approach relies on platform outages to isolate the effect of Robinhood investors over intraday horizons, and we specifically emphasize the high attention stocks that Robinhood investors often favor, which may help explain the differential implications for market quality.

2. Data and Descriptive Statistics

2.1 The Robinhood Ownership Sample

Until late 2020, Robinhood publicly displayed the aggregate number of users (investors) that held each stock on their webpages, updated at approximately one-hour intervals. We gather breadth of ownership data for Robinhood brokerage investors from Robintrack, an independent website that uses the Robinhood API to identify and record Robinhood investor interest for stocks with non-zero positions. Robintrack began gathering data in July of 2018, and the data end in August of 2020, when Robinhood ended the practice of reporting number of users.[8] Since our research focuses on the financial market implications of zero-commission investors, we focus on the January-August 2020 sample due to the large number of Robinhood investors during this period.[9]

[8] Robinhood ended the practice of displaying number of users in part due to the actions of Robintrack, voicing concerns that the information might be used to disadvantage Robinhood investors (e.g. Ponczek, 2020).
[9] Specifically, the sample period begins on January 16th, as the Robintrack data are unavailable at the beginning of January 2020, and ends on August 13th, 2020, when Robinhood discontinued displaying the number of owners.

The Robintrack data contain hourly stock-level investor position snapshots. We focus on observations reported between 9:00 AM to 4:00 PM EST on valid trading days identified in the Center for Research in Securities Prices (CRSP) data. We measure holdings changes for horizons longer than an hour by summing hourly holding changes.[10] The Robinhood sample is merged by common stock ticker and date with matches found in (CRSP) as well as from the NYSE's Trade and Quote (TAQ) database. Our identification strategy focuses on stocks with the potential for high expected Robinhood trading, and we therefore exclude stocks with few Robinhood owners. In particular, we require an average of 500 Robinhood owners during the week prior to each outage, with a minimum of 50 users each day (we also consider an alternative hurdle of 1,000 owners). The resulting dataset is comprised of over 4,000,000 stock-day observations during the Jan-Aug 2020 sample period. We use these data to compute several measures of Robinhood ownership, including the change in a stock's Robinhood users, to proxy for the level of Robinhood investors' interest in a stock. We describe these variables, along with all others used in our analysis, in Appendix A.

2.2 *Measuring Aggregate Retail Trading*

In addition to the Robinhood trading variables, we measure aggregate retail investor trading using the methodology of Boehmer, Jones, Zhang, and Zhang (2020) (BJZZ). Their approach exploits two key institutional features of retail trading. First, most equity trades by retail investors take place off-exchange, either filled from the broker's own inventory or sold by the broker to wholesalers (Battalio, Corwin, and Jennings, 2016). TAQ classifies these types of trades with exchange code "D." Accordingly, we measure aggregate retail trading by limiting our analysis to

[10] Stock-day observations with missing data are filled in with the value of the most recent valid observation within three trading days, otherwise it is left as missing.

trades executed on exchange code "D." Second, retail traders typically receive a small fraction of a cent price improvement over the National Best Bid or Offer (NBBO) for market orders (ranging from 0.01 to 0.2 cents), while institutional orders tend to be executed at whole or half-cent increments. Thus, we follow BJZZ and identify trades as retail purchases (sales) if the off-exchange trade took place at a price just below (above) a round penny.

2.3 Measures of Market Quality and High Frequency Trading

We construct several measures of financial market liquidity from high-frequency TAQ data. Quoted Spread is the best bid-ask spread scaled by the midquote; Effective Spread is an estimate of the percentage cost for a round-trip transaction. Specifically, the effective spread of the k^{th} trade is defined as $2\times|\ln(P_k) - \ln(M_k)|$, where P is the trade price and M is the prevailing midquote. Realized Spread is designed to capture the temporary component of the effective spread, and it is defined as $2\times D_k(\ln(P_k) - \ln(M_{k+5min}))$, where M_{k+5min} is the prevailing midquote five minutes after the k^{th} trade and D_k is a buy or sell indicator using the Lee and Ready (1991) algorithm. Price Impact captures the permanent component of the effective spread, defined as the percentage change in the mid-quote from right before to five minutes after the transaction. $2\times|\ln(M_{k+5min}) - \ln(M_k)|$. We also construct a return volatility measure based on the intraday standard deviation of stock trade-based returns obtained from TAQ. The measures are constructed in five-minute intervals for each firm, and the liquidity measures represent equal-weighted means for each stock within the five-minute windows.

To proxy for algorithmic and high-frequency trading, we compute three additional quote and trade based measures using NASDAQ TotalView ITCH data. Our first measure follows Chordia and Miao (2020) to identify high algorithmic activity by using the Strategic Runs measure from Hasbrouck and Saar (2013), which is constructed using the number of simultaneous runs occurring during each time period in the sample. Strategic runs, as defined in Hasbrouck and Saar (2013), are chains of consecutive order submission, cancellations, and executions with identical order sizes on the same side of the order book, where follow-up submissions occur within 100 milliseconds of each order cancellation. To increase the likelihood that a run is the result of a trading algorithm, runs are required to be at least 10 messages long. We time-weight runs based on the amount of time the run is in force, reported at each 5-minute period in the sample. We compute two additional proxies of HFT activity which are analyzed in Weller (2018), namely Order Volume / Trade Volume and the Cancel-Trade Ratio.[11] All three of these measures are positively related to HFT activity.

Our analysis also relies on measures of dealer inventory buildup, which we infer from imbalances in liquidity-demanding trades and liquidity-supplying orders. Specifically, we construct trade imbalance as the absolute dollar volume difference between buy trades and sell trades during a 5-minute period, scaled by the total dollar volume traded during the period. Using NASDAQ order-level data, we calculate the depth imbalance, which is defined as $|(P_{t,DW,O} - M_t) - (M_t - P_{t,DW,B})| / M_t$, where $P_{t,DW,O}$ and $P_{t,DW,B}$ reflect the depth-weighted (*DW*) average limit order price at time *t* of the offer, O, and bid, *B*, sides of the limit order book, and M_t represents the quoted midpoint. Depth imbalance is updated for every order and trade submitted at a nanosecond frequency, time-weighted by the duration of the depth value and reported (in basis points) in 5-minute bins. To reduce the influence of extreme outliers, the depth-weighted limit order prices are constructed after removing stub quotes beyond 20% of the quoted midpoint, and winsorizing the 99th percentile of orders according to order size.

[11] We do not consider the order-size based proxies of HFT activity from Weller (2018) as retail traders may also trade in odd-lot sizes.

We source market participant identifier (MPID) quote data from ITCH and identify market maker quotes in a manner similar to Hagströmer and Nordén (2013). We tag each MPID affiliation according to whether the market maker has a payment for order flow arrangement with Robinhood, which then allows us to measure the quoted spread and imbalance of each HFT market maker that is directly impacted by Robinhood outages. Table IA1 in the Internet Appendix lists the set of Robinhood-affiliated HFTs (Citadel, Virtu, G1X, Two Sigma, and Wolverine) and the remaining set of Nasdaq and FINRA member market makers.[12]

2.4 Sample Statistics

Table 1 presents summary statistics for Robinhood stocks. The unit of observation is stock-week, and we focus on stocks with an average of 500 Robinhood owners (and a minimum of 50) over the previous week. Observations are averaged across stocks each week and then across weeks. We observe that stocks are owned by 5,252 Robinhood investors on average, although the distribution is quite skewed, with an interquartile range of 132 to 1,734 owners. The average stock has 46 unique mentions on WallStreetBets per week, although this is similarly skewed, with the 75th percentile having only 7.4 mentions.

To get a sense of Robinhood investor preferences, Table IA2 in the Internet Appendix reports variable means for quintiles formed based on Robinhood ownership. From the variation across quintiles, we observe that Robinhood users tend to invest in large, high-volume, growth stocks. Aggregate retail volume (measured using the approach in BJZZ) from the previous week is positively correlated with Robinhood ownership, suggesting that Robinhood users tend to own the same stocks that retail investors in general trade. Moreover, we see that WallStreetBets

[12] Although market makers may also quote anonymously, FINRA 4613(A) and exchange rulebooks require market makers to have a continuous presence of identifiable quotes.

mentions are much higher for stocks with high Robinhood ownership, consistent with the notion that WallStreetBets mentions help drive Robinhood trading. The sorts also illustrate how Robinhood ownership relates to market quality and high frequency trading. In particular, Robinhood investors tend to trade in stocks with lower percentage spreads, more volatile stocks, and those with greater HFT activity.

3. Are Zero-Commission Investors Noise Traders?

Robinhood investors tend to be younger and less experienced than previously studied retail investors. For example, Robinhood's average investor is 31 years old with an account balance ranging from $1000 to $5000 (Venkateswaran, 2019). In contrast, the average retail investor in the heavily studied US retail brokerage sample from the 1990s (e.g. Barber and Odean, 2001) is considerably different. In that dataset, the average investor was 50 years old with an account balance of $47,000. Research suggests that young investors are less financially literate (Van Rooij, Lusardi, and Alessie, 2011) and more prone to behavioral mistakes (Goetzmann and Kumar, 2008; Dhar and Zhu, 2006).

We offer descriptive evidence on the sophistication of Robinhood investors by studying patterns in retail broker website traffic. In particular, we obtain web traffic information (for January through June of 2020) from AlexaInternet and SimilarWeb and compare Frequently Asked Questions (FAQs) visits at Robinhood relative to four other major retail brokerages (Charles Schwab, E*Trade, Fidelity, and TD Ameritrade). The findings are tabulated in Table IA3 in the Internet Appendix. Consistent with lack of expertise, the three most common FAQs pages visited by Robinhood investors are: "What is the Stock Market," "What is the DJIA," and "What is the S&P 500." In contrast, the most common FAQs at the other major retail brokers are slightly more complex, for example "What are Stock Splits," "What is an ETF," and "What are Puts and Calls."

Moreover, the FAQs pages are visited more often at Robinhood than at the other brokers, 6.1 visits per thousand for the top three FAQs topics at Robinhood vs. 1.5 per thousand visits for the top three topics at the other brokers. We acknowledge that brokers may feature FAQs information differently on their websites, and the descriptive evidence presented here is merely suggestive. We next examine relation between changes in Robinhood ownership and future returns to explore whether Robinhood trading is better described as skilled or noise.

3.1 The Informativeness of Robinhood Investor Trading

Recent evidence suggest that retail order flow positively predict stock returns (Kaniel, Saar, and Titman, 2008; Kaniel, et al., 2012; Kelley and Tetlock, 2013, 2017; Barrot, Kaniel, and Sraer, 2016; Boehmer et al., 2020; Farrell, et al., 2020). We examine whether this evidence holds for our sample period and whether it extends to Robinhood investors. To do so, we estimate cross-sectional regressions in the spirit of Fama and MacBeth (1973), in which we regress future stock returns on retail trading proxies, plus controls. Point estimates of the regression coefficients are the time-series averages of the daily coefficients. Newey-West standard errors are used to correct for autocorrelation in the time series of the Fama-MacBeth regression coefficients. We set the number of daily lags equal to two times the horizon of the dependent variable to account for overlapping return observations.

Our regression model for predicting holding period returns from day d to day $d+\tau$ is:

$$Ret_{i,[d,d+\tau]} = \alpha + \beta_1 RH_{i,d-1}^{Change} + \beta_2 AggRetailOIB_{i,d-1} + \beta_3 Control_{i,d-1} + \varepsilon_{i,[d,d+\tau]}. \quad (1)$$

The variable $RH_{i,d-1}^{Change}$ is the change in Robinhood ownership for stock i measured over the previous five trading days, standardized cross-sectionally. The coefficient on Robinhood ownership change, β_1, is of primary interest. We include the aggregate retail order flow measure proposed by Boehmer et al., (2020), measured over the previous week, to examine how retail trading in general predicts returns in our sample period. We also include two sets of control variables that are known predictors of returns: the past return matrix of $Ret_{[d\text{-}1]}$, $Ret_{[d\text{-}2]}$, and $Ret_{[d\text{-}6,d\text{-}2]}$, as well as the firm characteristics *Market Cap*, *Book-to-Market*, and *Skewness*.

Table 2 reports the regression estimates. The central result from Table 2 is that changes in Robinhood ownership do not positively predict future stock return at alternative horizons up to 20 days. Panel A of the table uses the weekly change in the number of Robinhood owners and Panel B of the table uses percentage changes in the number of owners. The estimated coefficients on Robinhood ownership with no control variables are generally negative and none are significantly positive. Controlling for other return variables and firm characteristics does not change the inference. Thus, there is no evidence that Robinhood investors on average are informed about future returns. This result is in contrast to the predictability of order flow from a broader set of retail investors. Across all specifications, aggregate retail order imbalances positively and significantly predict future stock returns, consistent with prior findings. In summary, although retail trades in general positively predict future returns, Robinhood investors on average appear to behave as noise traders.

4. The Effects of Zero-Commission Investors on Financial Markets

The evidence in Section 3 is consistent with Robinhood investors behaving as uninformed traders. The effects of noise traders on financial markets is unclear. Adverse selection microstructure models such as Glosten and Milgrom (1985) and Kyle (1985) suggest an increase in noise trading reduces the likelihood that market makers face informed traders, which should lead to improved market liquidity. In contrast, inventory risk models such as Ho and Stoll (1981) and Grossman and Miller (1988) emphasize that market makers are concerned about fluctuations in their inventory's value, which may be magnified by noise trading shocks. In this setting, an increase in noise trading can result in reduced liquidity. In addition, noise trading models such as DeLong et al. (1990), Campbell and Kyle (1993), and Llorente et al. (2002) predict that noise traders contribute to market volatility.

4.1 Identification Approach

Identifying the effect of retail investors on stock market liquidity is challenging because trading activity is endogenous and may itself be driven by liquidity (e.g. Foucault, Sraer, and Thesmar, 2011; Peress and Schmidt, 2020). Our approach for isolating the effects of zero-commission investors on financial markets relies on Robinhood platform outages. A unique and important element of our empirical setting is that financial markets are open for trading, allowing us to observe market quality, but a considerable number of zero-commission investors are unable to participate due to technical difficulties with the Robinhood platform.

4.1.1 Robinhood Platform Outages

Robinhood has experienced several outages during our sample period (e.g. Smith, 2020).[13] We identify these outages using Downdetector, a web platform that compiles user complaints (downdetector.com). Outage information is updated at 15-minute time intervals and reflects both external user reports and internal verification checks.[14] To ensure that the scale of an outage is material, we require a minimum of at least 200 outage reports during each 15-minute window that

[13] In their Administrative Complaint against Robinhood (E-2020-0047), the Commonwealth of Massachusetts stated that Robinhood experienced as many as 70 disruptions to their platform during January-November of 2020. Examples include March 9th, 2020, when Robinhood Help tweeted "Trading is currently down on Robinhood and we're investigating the issue." https://twitter.com/AskRobinhood/status/1237016846282280961, and June 18th, 2020, during which Robinhood Help tweeted "We're currently experiencing issues with our services and are investigating the issue." https://twitter.com/AskRobinhood/status/1273645742507216898..

[14] "Downdetector collects status reports from a series of sources… Our system validates and analyzes these reports in real-time, allowing us to automatically detect outages and service disruptions in their very early stages." https://downdetector.com/about-us/

markets are open. The filters result in 128 individual 15-minute windows reported on Downdetector.[15] Combining consecutive outage reports results in 25 unique outage episodes spanning approximately 1,920 trading minutes. This suggests that the Robinhood platform experienced an outage in some form for approximately 3.3% of the open market time during our sample period. Figure 1 illustrates the days on which outages occur (in grey bars) alongside Robinhood investor trading. Although the March outages generally coincide with a period of high trading, outages appear fairly randomly distributed over time.

4.1.2 Measuring Expected Robinhood Trading

Although Robinhood platform outages create clear negative shocks to zero-commission investor participation, analyzing their effects on financial markets requires a forecast of which stocks Robinhood traders would have traded in the absence of the outage. We consider two proxies for expected Robinhood trading based on message board activity and lagged trading. Our primary measure is constructed using data collected from the Reddit WallStreetBets message board (r/wallstreetbets). We use an automated script to parse the WallStreetBets forum, and we obtain all the posts and comments for the year 2020. Using a regular expressions processor, or 'regex', we search the text of each post and comment to identify patterns that reveal mentions of individual stocks (Appendix B provides details). For our outage analysis, we compute each stock's WallStreetBets measure as the number of unique forum users who post or comment in reference to the stock over the five days preceding the outage.

[15] Downdetector reports 17 outages during 2017-2019, considerably lower than the 128 reports in our 8-month sample of 2020, consistent with Robinhood facing technical difficulties due to the growth in users. In unreported analysis, we consider filters of 100, 500, and 1000 reports which result in outages of 2985, 1260, and 855 minutes respectively during our sample period. The results with these filters are quantitatively similar.

We also consider a proxy for expected Robinhood trading based on previous Robinhood trading activity. In particular, we identify stocks in the top quintile using information on absolute hourly changes in Robinhood ownership measured over the previous trading week. Figure 2 examines the relation between WallStreetBets activity and zero-commission traders as well as aggregate retail trading more generally. Specifically, we consider stocks in the top quintile of WallStreetBets mentions on each day *t*, and in Figure 2 we plot average changes in Robinhood ownership, percentage changes in Robinhood ownership, and aggregate retail trading (using the BJZZ measure), for days *t*-10 through *t*+10.[16] The patterns highlight the importance of WallStreetBets for retail traders, and Robinhood investors in particular. The first two panels illustrate that stocks with high WallStreetBets mentions experience a spike in Robinhood trading activity, which peaks a few days after the period of high WallStreetBets activity.

The third panel of Figure 2 depicts a markedly different pattern for aggregate retail trading. In particular, aggregate retail volume leads WallStreetBets mentions by a couple of days and therefore also leads Robinhood activity by nearly a week. The plots consider unsigned volume, and therefore it is possible that Robinhood investors are trading in different directions than other retail investors. In Figure IA1 in the Internet Appendix, we sort based on signed aggregate retail order flow, and we create analogous plots for top quintile buys and sells. The plots confirm that Robinhood investors tend to trade on the same side of the market as other retail investors, but roughly one to three days later. The delayed pattern may help explain why changes in Robinhood ownership do not exhibit the same positive relation with future returns observed with aggregate retail order flow in Table 2.

[16] Abnormal activity on days -10 to +10 are estimated relative to a 20-day moving average benchmark from day -30 to -11, standardized to the interval -1 to 1 (to control for any potential time trend).

We also construct plots analogous to Figure 2, but ones that are a function of Robinhood ownership changes, rather than WSB activity. In particular, Figure IA2 in the Internet Appendix plots the pattern of Robinhood trading after sorting stocks into top quintile changes in Robinhood ownership portfolios at the daily level. We observe a pattern consistent with Figure 2, in that stocks with high Robinhood trading on day t continue to have significantly elevated trading on days t+1 through t+5, whereas aggregate retail trading for these stocks peaks on day t-3. The persistence in Robinhood trading gives credence for subsequent analysis that proxies for expected Robinhood trading during outages using Robinhood ownership changes from the days preceding the outage. The patterns for level changes in Robinhood ownership and percentage changes in ownership are very similar, and for brevity we relegate evidence for percentage changes in ownership to the internet appendix going forward (e.g. Table IA4).

Table 3 reports summary statistics of key variables sorted by the two expected Robinhood activity measures. For each measure and for each week of the sample, we sort the 2,015 Robinhood stocks into two groups, those below the top quintile and those in the top quintile of expected Robinhood activity.[17] We then average across the two groups across all weeks in the sample period, providing a sense of the average outage analyzed in the following analysis. The WallStreetBets activity measure and the changes in Robinhood Ownership variable capture similar stocks, as both are positively correlated with size, trading volume, and aggregate retail volume. In our subsequent analysis, we isolate the effects of zero commission investors on financial markets by contrasting the effects of Robinhood outages on stocks with high (top-quintile) expected Robinhood trading activity with the remaining set of stocks in our sample. Our approach includes

[17] Not all Robinhood stocks are actively traded by Robinhood investors throughout the sample period, which results in fewer than 2,015 stocks in some weeks. In addition, the number of stocks in the top quintile for the two Robinhood trading proxies occasionally differs due to some weeks with fewer stocks being actively discussed on WallStreetBets.

firm and day fixed effects to help control for systematic market quality differences across firms or over time.

4.2 Robinhood Platform Outages and Trading Activity

We begin by exploring whether Robinhood platform outages impact trading activity. Our approach relies on the following model, estimated with OLS regressions:

$$Trd_{i,t} = \alpha + \beta_1 RH_{i,d-1} + \beta_2 Outage_t + \beta_3 RH_{i,d-1} \times Outage_t + \gamma_i + \delta_d + \varepsilon_{i,t}. \qquad (2)$$

The sample consists of 5-minute intervals, t, for each firm i during the window on day d when the Robinhood platform experiences an outage, matched with 5-minute intervals for the same stock and time for each of the 5 trading days preceding the outage date. The dependent variable, $Trd_{i,t}$, represents trading activity, and we consider three alternative measures, trading volume, trading intensity (the number of trades), and a proxy for retail trading from sources in addition to Robinhood (aggregate retail volume). The $RH_{i,d-1}$ variable is an indicator for stocks in the top quintile of expected Robinhood trading. We consider two proxies for expected Robinhood trading: the number of unique WallStreetBets mentions of stock i over the previous five trading days, and the absolute change in the number of Robinhood owners over the previous five trading days. We also include firm, γ_i, and day, δ_d, fixed effects in the model.

Table 4 presents the estimated slope coefficients and associated t-statistics, which we compute with standard errors that are heteroskedastic robust and clustered by firm and day (Petersen, 2009). The first three columns present results during the Robinhood outages. The key estimated coefficient is for the interaction between $RH_{i,d-1}$ and $Outage_t$ which estimates how the trading measures are impacted by outages for high Robinhood stocks (relative to other Robinhood stocks). We observe that trading activity drops significantly during outages for high Robinhood stocks. For example, Robinhood outages coincide with 6.2% fewer trades for Robinhood stocks using the WallStreetBets proxy and 7.7% fewer trades using the lagged Robinhood trading proxy.

To help gauge whether the economic magnitudes in Table 4 are reasonable, we note that Robinhood reported 4.21 million daily average revenue trades (DART) in June of 2020, comprising 33% (and the largest fraction) of the total DART reported among TD Ameritrade, Interactive Brokers, Charles Schwab, and E*Trade (Basak, 2020). In addition, Fitzgerald (2020) and Winck (2020) report that retail traders often account for 20-25% of stock market activity. Although this evidence is aggregate and anecdotal, together it supports the plausibility of platform outages having a material effect on Robinhood stocks.[18]

To address concerns that the outage effects may be spurious, we repeat the analysis for the pseudo-events in the last three columns of Table 4. The empirical approach is identical to specifications presented in the first three columns, except that we assume that the pseudo outage occurs one hour after the actual outage ends. The pseudo-event length is assumed to be 60 minutes or the length of the actual outage, whichever is greater, but it is required to take place on the same trading day as the outage. The estimate coefficients on the interaction between $RH_{i,d-1}$ and $Outage_t$ are close to zero and statistically insignificant, regardless of specification, suggesting that the drop in trading activity we observe for high Robinhood stocks is unique to the outages.

4.3 Robinhood Platform Outages and Market Liquidity

[18] Table 4 suggests that Robinhood outages have a stronger effect on overall trading than aggregate retail trading. It is possible that investors with accounts at other retail brokerages have elevated trading in stocks with high expected Robinhood trading, which lessens the drop in aggregate retail trading. Moreover, we show in Section 5 that HFT activity is particularly sensitive to Robinhood trading, which may help explain the significant drop in overall market volume during outages.

Having established that Robinhood materially impacts trading activity, we next consider whether Robinhood trading is significantly related to market quality. We first consider the effects on stock liquidity by estimating the following model:

$$Liquidity_{i,t} = \alpha + \beta_1 RH_{i,d-1} + \beta_2 Outage_t + \beta_3 RH_{i,d-1} \times Outage_t + \gamma_i + \delta_d + \varepsilon_{i,t}. \quad (3)$$

This model is similar to Equation (2) except the dependent variable represents alternative measures of stock liquidity. Specifically, we analyze the effects of Robinhood platform outages on *Quoted Spread*, *Effective Spread*, *Realized Spread*, and *Price Impact* for the stocks with the greatest expected trading by Robinhood investors. As before, we create indicator variables for stocks in the top quintile using the two measures of Robinhood expected trading: the WallStreetBets proxy (Panel A of Table 5), and the change in Robinhood ownership (Panel B of Table 5).

The first four columns in Table 5 present the estimated slope coefficients and *t*-statistics for the Robinhood outages. Regardless of the Robinhood trading proxy, spreads and price impact are significantly lower during the outages for the high Robinhood stocks. Since these variables measure illiquidity, the results suggest that liquidity improves when Robinhood investors are unable to trade due to the outage. We confirm in the last four columns of Table 5 that the significant liquidity effects disappear if we instead use pseudo-outages that are one hour after the actual outages end.

4.4 Robinhood Platform Outages Price Volatility

We next examine whether Robinhood trading influences stock return volatility by analyzing Robinhood platform outages with the following model:

$$Volatility_{i,t} = \alpha + \beta_1 RH_{i,d-1} + \beta_2 Outage_t + \beta_3 RH_{i,d-1} \times Outage_t + \gamma_i + \delta_d + \varepsilon_{i,t}, \quad (4)$$

where $Volatility_{i,t}$ is measured from individual transaction prices for firm *i* during each five minute window *t*. The independent variables are the same as those in Equation (2) and (3). We present the estimates of this model in Table 6. Panel A of Table 6 presents the results using WallStreetBets mentions as the proxy for expected Robinhood trading, and Panel B relies on lagged Robinhood trading as the proxy for expected Robinhood trading. For both proxies, platform outages are associated with significantly lower volatility for high Robinhood stocks, suggesting that an exogenous reduction in Robinhood traders leads to less volatility. The analogous evidence for pseudo outages is economically negligible and statistically insignificant, confirming that the volatility results hold only during actual platform outages.

4.5 Robustness

An important potential concern in our setting is that Robinhood outages may reflect capacity constraints that are reached during episodes of heightened market activity, and therefore outages may be endogenous with market quality.[19] The complete lack of evidence for pseudo-events measured one hour after actual events helps mitigates this concern. However, in this section, we perform a number of additional robustness checks. We begin by repeating the analysis in Tables 4-6 using absolute percentage changes (instead of level changes) in hourly Robinhood ownership over the previous five trading days as the proxy for expected Robinhood trading during platform outages. The findings are tabulated in Table IA4 in the Internet Appendix and are very similar to the evidence in Tables 4-6.

We next partition the sample in a number of ways to help address concerns that platform outages are not exogenous. The results are presented in Table 7, where for brevity we report only the interaction term that captures the effect of outages on stocks with high expected Robinhood trading (full regression results are reported in Table IA5 in the Internet Appendix). One concern is

[19] Platform capacity constraint issues may arise due to server capacity, hardware failure, software efficiency, or other issues related to platform overload.

that outages may be driven by a small number of firms with attention-grabbing news (such as IPOs or firms with bankruptcy news). By excluding high-news stocks from the analysis, we are able to examine the effects of platform outages on other firms that are unrelated to the cause of the outage but nevertheless impacted by it. In Panel A of Table 7, we exclude stocks that exhibit a 20% or more increase in the number of WallStreetBets mentions on the day of the outage relative to the lagged 5-day average. The market quality evidence continues to be robust, suggesting that firm-news-driven outages are not a serious concern.

We next consider the possibility that outages may be particularly susceptible to after-hours market news or volatility during the market opening by excluding outages that begin before 9:45 AM (Panel B of Table 7). Additionally, well-publicized Robinhood outages occurred on the days of March 2^{nd}, 3^{rd}, and 9^{th}, when markets experienced high volatility due to the developing Covid-19 pandemic. To ensure the results are not driven by this period, we repeat the analysis after excluding all outages that occurred in March of 2020 (8 of the 25 outage events, Panel C of Table 7). Although statistical significance weakens in some cases, these tests do not support the view Robinhood outages are driven by market news that leads to spurious effects on market quality.

We also confirm the robustness of the comparison windows. The pseudo-outages are assumed to occur one hour after the actual event. However, some outages in the sample either last long enough, or occur late enough in the afternoon, that an equal length pseudo outage cannot be formed on the same trading day. This results in a pseudo sample with fewer observations, and therefore less statistical power, than the Robinhood sample of interest. In Panel D of Table 7, we report the results from our analysis in which we only include observations from an equal observation subsample, formed by decreasing the length of each Robinhood outage to match the length of the pseudo window. The outage results remain robust.

Our benchmark period is measured using the week prior to the outage, and the evidence in Figure 2 of heightened aggregate retail trading during this period may raise concerns that the benchmark may not be representative. Therefore, in Panel E of Table 7, we repeat the analysis using a pre-outage benchmark window from day -10 through day -6, instead of days -5 through -1. The findings survive this robustness test. In Panel F, we raise the threshold for the average number of Robinhood users owning the stock from 500 to 1000. Again, the findings remain robust.

Our final important robustness check plots the time-series of market quality measures before, during, and after outages. Analogous to the difference-in-differences analysis, we construct the measures separately for stocks with high expected trading (top quintile mentions on WallStreetBets) and the remaining set of Robinhood stocks. We measure the market quality measures on the outage date relative to the average during that time of day over the benchmark period of the previous five days, and we standardize the differences by dividing by the standard deviation of the benchmark observations. This sample is comprised of the ten outages that occur after 10:00am and that are reported by Downdetector as lasting no longer than 15 minutes (i.e. where complaints fall to below 200 within fifteen minutes).

Figure 3 plots the abnormal market quality measures for each five-minute interval over the period spanning 45 minutes before the outage to 45 minutes after the outage begins. The plots provide additional evidence that the outages serve as exogenous shocks. In particular, the plots highlight that volume, illiquidity, and volatility drop for stocks with high expected Robinhood trading precisely during the outage window reported on Downdetector, while remaining relatively flat for the control set of firms. Moreover, the plots do not add credence to concerns of a lack of parallel trends prior to the outage, and market conditions begin to return to normal fairly quickly after the outage ends and Robinhood investors are able to trade. Overall, the robustness checks provide convincing support for the interpretation that Robinhood platform outages have causal effects on financial markets.

5. Zero-Commission Investors and High Frequency Traders

The evidence in the previous section that Robinhood outages are associated with improvements in market quality raises the question of how off-exchange trading influences measures of public market quality. Although off-exchange retail trading occurs in dark markets, trading must be reported to FINRA within ten seconds.[20] However, the more natural path for dark trading to influence lit market quality is through the high frequency trading firms that make markets for zero-commission investors. Payment for order flow arrangements have existed for decades (e.g. Battalio, 1997; Bessembinder and Kaufman, 1997). In recent years, however, the HFT firms that provide liquidity to retail orders off exchange have also become the largest market makers on public markets as well,[21] which suggests that information about zero-commission trading may influence lit market quality directly through these firms' algorithms.

FINRA regulation 5320, which prohibits front-running of customer orders, requires that HFT firms implement information barriers to prevent market making units from obtaining knowledge of customer orders held by their wholesale (payment for order flow) units. However, algorithms for both units are influenced by the firm's overall position and internal risk tolerance in the stock. If the firm reaches a threshold for inventory capacity, each unit's appetite for risk will adjust accordingly. As a result, shocks to the operations of the wholesale unit may influence

[20] https://www.finra.org/filing-reporting/market-transparency-reporting/trade-reporting-faq#102

[21] For example, Virtu Financial acquired Cohen Capital in 2011 and Citadel acquired KCG's market making business in 2016. Currently Virtu and Citadel, which both internalize orders for Robinhood, are two of the three designated market maker firms on NYSE.

liquidity provision by the market making unit. We explore this channel by studying HFT activity in general as well as analyzing individual market maker quoting behavior.

5.1 Robinhood Platform Outages and HFT Behavior

We begin by exploring the direct effects of Robinhood outages on HFT activity using the following model:

$$HFT_{i,t} = \alpha + \beta_1 RH_{i,d-1} + \beta_2 Outage_t + \beta_3 RH_{i,d-1} \times Outage_t + \gamma_i + \delta_d + \varepsilon_{i,t}. \qquad (5)$$

The dependent variable represents the three alternative HFT proxies introduced in Section 3.2: Strategic Runs, the Order Volume to Trade Volume ratio, and the Cancel to Trade ratio. The independent variables are unchanged from Equations (2) through (4).

Table 8 present results for the platform outage periods as well as the pseudo-outage windows. We observe that for both proxies of high expected Robinhood trading, the outages are associated with significantly lower HFT activity for all of the HFT activity measures. The evidence is consistent with HFTs pulling back and participating in markets less when Robinhood investors are not able to trade. The insignificant results for the pseudo-outages suggest that the drop in HFT activity is unique to the actual shock to Robinhood trading.

If the changes to market quality during outages are mediated by HFTs with payment for order flow arrangements with Robinhood, we would expect to observe changes specifically to their quoting behavior. Although dealer firms often quote anonymously, their algorithms govern their mandated publicly displayed quotes, and it is likely that material shocks to their zero-commission order flow would influence their identifiable quotes, which we identify with ITCH data (see Section 2.3). We explore this hypothesis in Table 9, which reports the results of estimating Equation (5) separately for bid-ask spreads measured from the quotes with the identities of Robinhood-affiliated dealers and non-affiliated dealers (listed in Table IA1 in the Internet

Appendix). The regression results show that for both proxies for high expected Robinhood trading, outages are associated with narrowing of dealer quoted spreads exclusively for Robinhood-affiliated market makers, consistent with the notion that market quality is affected through dealers with payment for order flow arrangements with Robinhood.

5.2 Robinhood Platform Outages and Market Quality: The Role of Inventory Risk

The underlying idea behind payment for order flow arrangements is that liquidity-providing HFT firms face considerably lower risks of engaging with informed traders when making markets for retail investors. As a result, HFTs are able to provide liquidity (off-exchange) at similar or better rates than available on public markets that include the larger adverse selection component, while still being able to accommodate rebates to the brokerage firm. This arrangement works best when trading is uncorrelated. However, if zero-commission investors often herd into and out of stocks, for example those discussed on WallStreetBets, it could lead to order imbalances that create inventory risk for the market makers (e.g. Ho and Stoll, 1981; Grossman and Miller, 1988). In this section, we analyze the effects of Robinhood outages on measures of market inventory imbalances. We also introduce a proxy for inventory risk based on autocorrelated Robinhood trading, and we explore whether increased inventory risk is associated with greater platform outage effects.

Table 10 estimates Equation (5) with alternative measures of inventory imbalances as the dependent variable. We consider trade-based imbalances as well as market-depth imbalances, which captures asymmetry in total depth around the midpoint of the best bid and ask. We also assess whether outages influence depth imbalances specifically for Robinhood-affiliated market makers. For both proxies of expected Robinhood trading, we observe that outages are associated with reduced trade order imbalances and lower market depth-weighted imbalances. In addition, focusing specifically on depth quoted by Robinhood-affiliated market makers, we find that outages lead to depth that is more centered around the midquote. In contrast, we find no significant changes when depth imbalance is measured using dealer quotes that are unaffiliated with Robinhood.[22]

Inventory risk is more likely to arise when zero-commission investors herd together, which can lead to autocorrelated order flow. In our final analysis, we proxy for inventory risk using lagged autocorrelation of changes in Robinhood ownership, and we examine whether Robinhood platform outages have larger effects on stocks with greater inventory risk. Specifically, we form quintiles based on the autocorrelation in hourly changes in Robinhood ownership over the five days prior to outages (excluding overnight changes). First, we note that zero-commission investors do tend to trade in similar ways. The average autocorrelation in hourly changes in Robinhood ownership for top quintile stocks is 0.191, compared with 0.134 for quintiles 1-4. As a benchmark, autocorrelation among traditional retail investors is lower, with the average autocorrelation of hourly BJZZ order flow being 0.099 for top quintile stocks and -0.031 for quintiles 1-4.

We investigate whether the effects of platform outages are stronger for stocks with greater Robinhood inventory risk using the following model:

$$\begin{aligned} MktQuality_{i,t} = {} & \alpha + \beta_1 RH_{i,d-1} + \beta_2 Outage_t + \beta_3 InventoryRisk_{i,d-1} \\ & + \beta_4 RH_{i,d-1} \times Outage_t + \beta_5 InventoryRisk_{i,d-1} \times Outage_t \\ & + \beta_6 RH_{i,d-1} \times InventoryRisk_{d-1} + \beta_7 RH_{i,t-1} \times \; IventoryRisk_{d-1} \times Outage_t \\ & + \gamma_i + \; \delta_d + \varepsilon_{i,t}. \end{aligned} \tag{6}$$

Equation (6) builds on earlier models by adding a triple interaction term that interacts high Robinhood activity and the Outage dummy variable with an indicator variable equal to one for

[22] Figure IA3 in the Internet Appendix plots quote and imbalance measures before, during, and after outages analogous to the approach in Figure 3. The plots show similar patterns as in Figure 3, with the measures reacting rapidly during the outage and returning to normal levels relatively quickly afterwards (with the exception of unaffiliated dealers quotes, which show little evidence of reacting to outages).

stocks in the top autocorrelation quintile. The dependent variable represents various measures of liquidity and order imbalances.

We present the estimates of the model in Table 11. Regardless of the Robinhood trading proxy, the results show that stock liquidity improves the most during outages for Robinhood stocks with the greatest autocorrelation in trading. Moreover, we observe that order imbalances fall more for high inventory risk stocks, and the relation holds at the dealer-level only for HFTs that purchase Robinhood order flow. These results support the view that zero-commission investors create inventory risks for Robinhood-affiliated HFTs that increase the costs of providing liquidity.

6. Conclusion

This paper studies the financial market implications of an increasingly important group of traders, zero-commission investors. Drawn to financial markets by Robinhood's industry-changing zero-fee trading model, no account minimums, and an easy-to-use interface, this new class of retail investors represents a significant change in the dynamics of retail trading. Using breadth of ownership data from Robinhood, we study zero-commission investors' trading performance, the impact they have on market quality, and how they interact with another important market participant, high frequency traders.

Our evidence suggests that zero-commission investors in aggregate behave as noise traders, as changes in Robinhood ownership are unrelated to future returns. These findings are in contrast to evidence that aggregate retail order flow, which includes retail traders across many brokers, positively predict stock returns. Although retail traders in aggregate appear to invest in the same types of securities that are popular among Robinhood investors, we find that the broader measure of retail trading leads Robinhood trading by several days.

We isolate the effects of zero-commission investors on financial markets by studying market quality during the Robinhood trading platform outages that occurred throughout 2020. An important element of the outages is that financial markets are open for trading, but zero-commission investors are restricted due to the platform difficulties. To forecast which securities Robinhood investors would have traded without the platform impediment, we measure stock mentions on the social media platform Reddit's WallStreetBets as well as lagged Robinhood stock interest.

Our analysis indicates that during platform outages when zero-commission trading is restricted, stocks favored by Robinhood users experience reduced bid-ask spreads and price impacts as well as lower return volatility, suggesting that Robinhood investors negatively impact market quality. The results do not appear to be driven by market conditions on days with abnormal activity. In particular, pseudo-events that are assumed to occur one hour after the actual outage are not associated with changes in market quality. Additionally, the results remain robust after a number of additional robustness checks, and plots around outages point towards a causal relation. The evidence convincingly supports the view that market quality improves for Robinhood stocks when outages restrict zero-commission traders.

Our final analyses examine the role HFTs play in mediating the effects of zero-commission trading on financial markets. We observe that quoted bid-ask spreads narrow during outages specifically for Robinhood-affiliated HFTs, highlighting the interaction between off-exchange trading and public market quality. Changes to order depths around outages suggest that zero-commission investors create unique inventory risks for Robinhood-affiliated dealers. Further, stocks with high inventory risk, as proxied by high autocorrelation in recent Robinhood order flow, experience the greatest improvements in market quality and reductions in trade and depth imbalances during Robinhood outages. Overall, the findings support the view that zero-commission traders can have negative effects on stock market quality, consistent with behavioral noise trader and inventory risk models.

Appendix A: Variable Definitions

A.1 Key Explanatory Variables

- *Robinhood Change* – Stock *i'*s change in Robinhood ownership measured over hourly and weekly horizons. Winsorized at 0.1% tails. Source: Web Scraping.
- *Robinhood % Change* – Stock *i'*s change in Robinhood ownership measured over hourly and weekly horizons. Winsorized at 0.1% tails. Source: Web Scraping.
- $RH_{i,d\text{-}1}$ – Variable to capture stocks with high expected Robinhood Trading based on two separate proxies:
  - $RH_{i,d-1}^{WSB}$ – An indicator variable equal to 1 if the stock is the top quintile of WallStreetBets mentions over the previous five trading days, based on the number of unique users that mention the stock in a post or comment on the Reddit forum WallStreetBets. Source: Web Scraping.
  - $RH_{i,d-1}^{\Delta RH}$ – An indicator variable equal to 1 if the stock is in the top quintile of absolute hourly changes in Robinhood ownership measured over the previous five trading days.
- *Outage* – An indicator variable that denotes periods experiencing Robinhood platform outages (1 if an outage occurs during period *t* and 0 otherwise). Source: Downdetector
- *Inventory Risk* – An indicator variable equal to 1 if stock *i* is in the top quintile based on the autocorrelation in hourly changes in Robinhood ownership over the previous five trading days (excluding overnight changes). Source: TAQ.

A.2 Outcome Variables

- *Return* (Table 2) – This variable represents security *i*'s return measured over various intervals. For example, *Return*[1,5] represents the return from day 1 through day 5. Source: CRSP
- *Trading Volume* (Tables 4, 7) – Natural log of the total share volume. Winsorized at 0.1% tails. Source: TAQ.
- *Trading Intensity* (Tables 4, 7) – Natural log of the total number of trades. Winsorized at 0.1% tails. Source: TAQ.
- *Aggregate Retail Volume* (Table 4) – Natural log of total retail volume, using Boehmer et al., (2020) to identify retail trades. Winsorized at 0.1% tails. Source: TAQ.
- *Quoted Spread* (Tables 5, 7, 11) – Equal-weighted average of best bid-ask spread (scaled by the midquote) during the intraday window. Winsorized at 0.1% tails. Source: TAQ.
- *Effective Spread* (Tables 5, 7, 11) – Equal-weighted average of the effective spread during the intraday window. For each transaction, the effective spread is defined $2\times|\ln(P_k) - \ln(M_k)|$, where P is the trade price and M is the prevailing midquote. Winsorized at 0.1% tails. Source: TAQ.
- *Realized Spread* (Tables 5, 7, 11) – Equal-weighted average of the realized spread during the intraday window. For each transaction, the realized spread is defined as $2\times D_k(\ln(P_k) - \ln(M_{k+5}))$, where D_k equals 1 for a buy transaction and -1 for a sell transaction and is valid 5

minutes after the kth transaction. Trade sign is based on Lee and Ready (1991) algorithm. Winsorized at 0.1% tails. Source: TAQ.

- *Price Impact* (Tables 5, 7, 11) – Equal-weighted average of the price impact. For each transaction, the price impact is defined as $2 \times D_k (\ln(M_{k+5}) - \ln(M_k))$, where M_{k+5} is the bid-ask mid-point five minutes after the kth transaction. Winsorized at 0.1% tails. Source: TAQ.
- *Volatility* (Tables 6, 7) – The trade-based standard deviation of returns during the 5-minute period, if have a minimum of 10 trades. Winsorized at 0.1% tails. Source: TAQ.
- *Strategic Runs* (Table 8) – The natural log of the time-weighted average of total number of strategic runs, where one strategic run is a series of submissions, cancellations, and executions with identical order sizes on the same side of the order book, and follow-up submissions occur within 100 milliseconds of each order cancellation. Runs are required to be at least 10 messages long. Winsorized at 0.1% tails. Source: Nasdaq TotalView ITCH.
- *Order Volume / Trade Volume* (Table 8) – The natural log of the ratio of total volume across all orders placed divided by the total volume traded. Winsorized at 0.1% tails. Source: Nasdaq TotalView ITCH.
- *Cancel-Trade Ratio* (Table 8) – The natural log of the ratio of the number of full or partial cancellations divided by the number of trades. Winsorized at 0.1% tails. Source: Nasdaq TotalView ITCH.
- *Robinhood Market Maker Spreads* (Table 9) – The average distance between the best bid and best offer of market makers that have payment for order flow arrangement with Robinhood. MPID is identified from Nasdaq TotalView ITCH (See Table IA1 for the list of Robinhood-affiliated Market Makers). Spreads are time-weighted for each MPID during each five-minute window, and then averaged across MPIDs. Winsorized at 99%.
- *Other Market Maker Spreads* (Table 9) – The average distance between the best bid and best offer of market makers that have payment for order flow arrangement with Robinhood. MPID is identified from Nasdaq TotalView ITCH (See Table IA1 for complete list of market makers that are unaffiliated with Robinhood). Spreads are time-weighted for each MPID during each five-minute window, and then averaged across MPIDs. Winsorized at 99%.
- *Trade Imbalance* (Tables 10, 11) – The absolute difference between the dollar volume of buy and sell trades, expressed as a percent of total dollar volume of buy and sell trades. Winsorized at 0.1% tails. Source: TAQ.
- *Depth-Weighted Imbalance* (Tables 10, 11) – The imbalance of resting limit orders. It is the absolute difference between the depth-weighted limit buy order price distance from the quoted midpoint and the depth-weighted limit sell order distance from the quoted midpoint, scaled by the quoted midpoint. Winsorized at 0.1% tails. Source: Nasdaq TotalView ITCH.
- *Robinhood Market Maker Depth Imbalance* (Tables 10, 11) – The depth-weighted imbalance for the orders with MPID attributions, where only orders from market makers that have payment for order flow arrangement with Robinhood are included. MPID is identified from Nasdaq TotalView ITCH (See Table IA4 for complete list of Robinhood Market Maker). Winsorized at 0.1% tails.
- *Other Market Maker Depth Imbalance* (Table 10) – The depth-weighted imbalance for the orders with MPID attributions, where only orders from market makers that *do not* have

payment for order flow arrangement with Robinhood are included. MPID is identified from Nasdaq TotalView ITCH (See Table IA4 for complete list of market makers that is non-affiliated with Robinhood). Winsorized at 0.1% tails.

A.3 Control Variables for Table 2

- *Aggregate Retail OIB* – The difference between retail buy and sell dollar volumes, divided by the sum of retail buy and sell dollar volumes. Retail trades are identified following the methodology of Boehmer et al., 2020. Winsorized at 0.1% tails. Source: TAQ.
- *Return* – This variable represents security *i*'s return measured over various intervals. For example, *Return*[-5,-1] represents the return from day -5 through day -1. Winsorized at 0.1% tails.
- *Market Capitalization* – Each security's price multiplied by the number of shares outstanding. We log transform market equity and lag it by one day. Winsorized at 0.1% tails. Source: CRSP.
- *Book-to-Market* – The ratio of book equity from the most recent fiscal year to the market equity from the past December. Winsorized at 0.1% tails. Source: Compustat and CRSP
- *Skewness* – The one-month idiosyncratic skewness of Harvey and Siddique (2000), calculated as the third moment of the residual obtained from the regression of the previous month's daily returns on excess market returns and squared excess market returns. Winsorized at 0.1% tails. Source: CRSP.

Appendix B: WallStreetBets Search Approach

We utilize the following search algorithm to identify single-stock mentions on the Reddit forum WallStreetBets. It is common to preface ticker symbols with a dollar sign when posting on WallStreetBets, and we search for $ticker symbols for each stock held by at least 50 Robinhood investors. In addition, since not all posts or comments use the format $ticker, we consider two additional search criteria. First, for tickers that do not overlap with acronyms, abbreviations, or initialisms, we search by the raw ticker without the $ preface, we then also consider additional search terms which are unique to a particular company for the 300 most popular stocks among Robinhood owners (representing approximately 80% of holdings). The three search methods compose a set of terms which can be used to identify the stock mentioned. Here are two search examples:

Company (Ticker)	Search by raw ticker	Other Unique Phrases	Search Algorithm Set
Ford Motor Company (F)	No	Ford, F-150	[$F, Ford, F-150]
Apple, Inc. (AAPL)	Yes	Tim Cook, iPhone, Macbook	[AAPL, $AAPL, Tim Cook, iPhone, Macbook]

The search algorithm set for each stock in the sample is unique, where we ensure there are no overlapping search identifiers shared between any two stocks. To identify stocks mentioned on WallStreetBets, we parse the text of each post and comment and match each word in the text against the search algorithm sets for all of the stocks in the sample. This method of searching for stock mentions by a unique search set is conservative in that may not capture all mentions of an individual stock. However, it minimizes the likelihood of misidentifying stock mentions.

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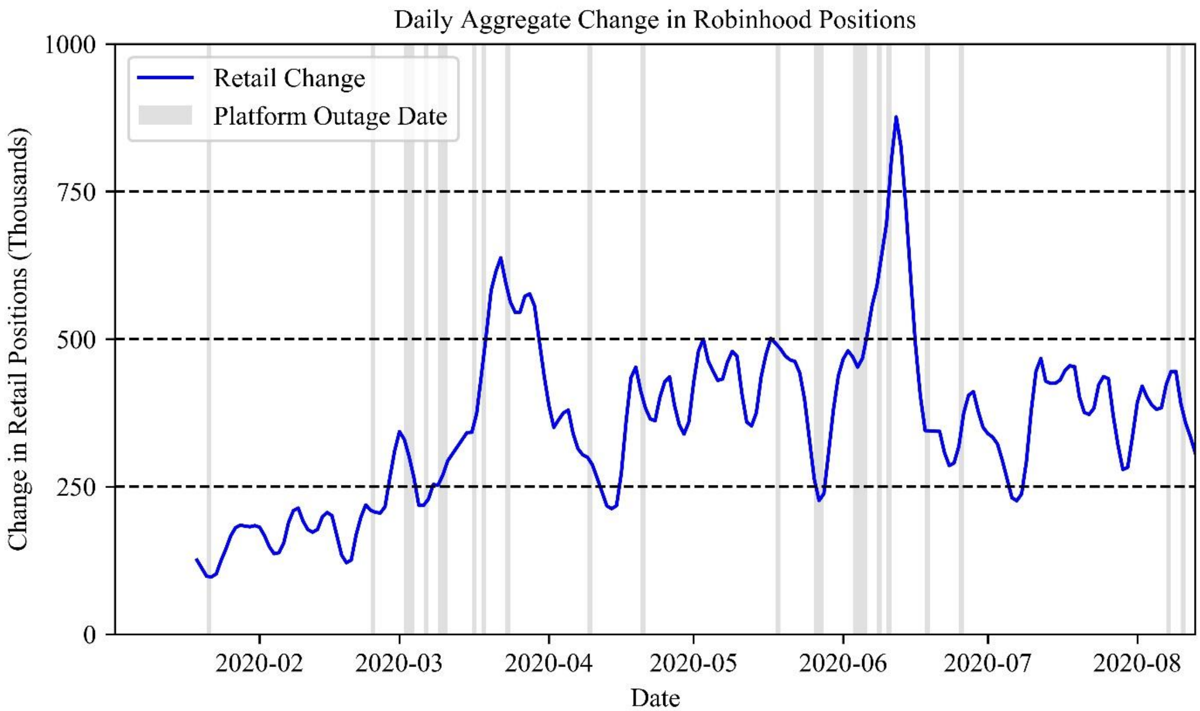

Figure 1. Changes in Aggregate Robinhood Positions and Platform Outage Dates. The figure plots the cumulative absolute value of hourly changes of Robinhood user positions (*Retail Change*) and the days in which the Robinhood platform experienced an interruption during the regular trading hours of 9:30 to 16:00 EST (*Platform Outage Date*) from Jan 16 to Sep 13, 2020. Platform outages are defined as having at least 200 outages on Downdetector.com.

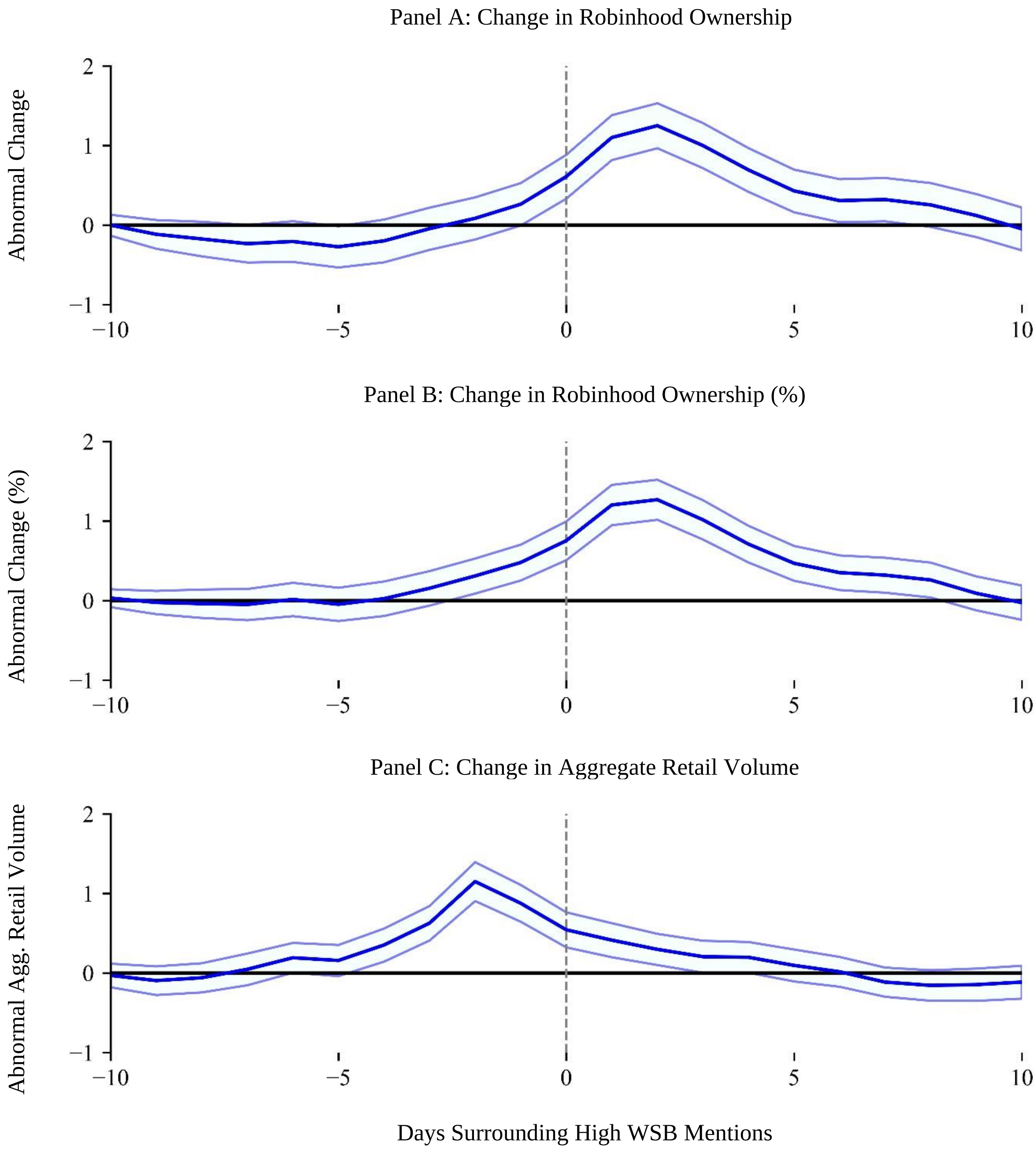

Figure 2. Retail Activity Surrounding Stock Mentions on the Reddit Forum WallStreetBets. High WallStreetBets (WSB) mention days are defined on day 0 as being in the top quintile of stocks according to the number of posts and comments by unique users on WallStreetBets. Abnormal activity on days -10 to +10 are estimated relative to a 20-day moving average benchmark from day -30 to -11, scaled by the standard deviation of the 20-day benchmark period. Estimates of abnormal activity are indicated by the solid blue line and are obtained from ordinary least squares regressions to remove firm fixed effects, where the shaded area surrounding the blue line indicates the 99% confidence interval. *Abnormal Change* is the increase in daily aggregate changes in hourly Robinhood positions relative to the benchmark, *Abnormal Change (%)* is an equivalent measure scaled by total Robinhood users, and *Abnormal Agg. Retail Volume* is the relative increase in aggregate retail volume using the classification described in Boehmer et al., 2020.

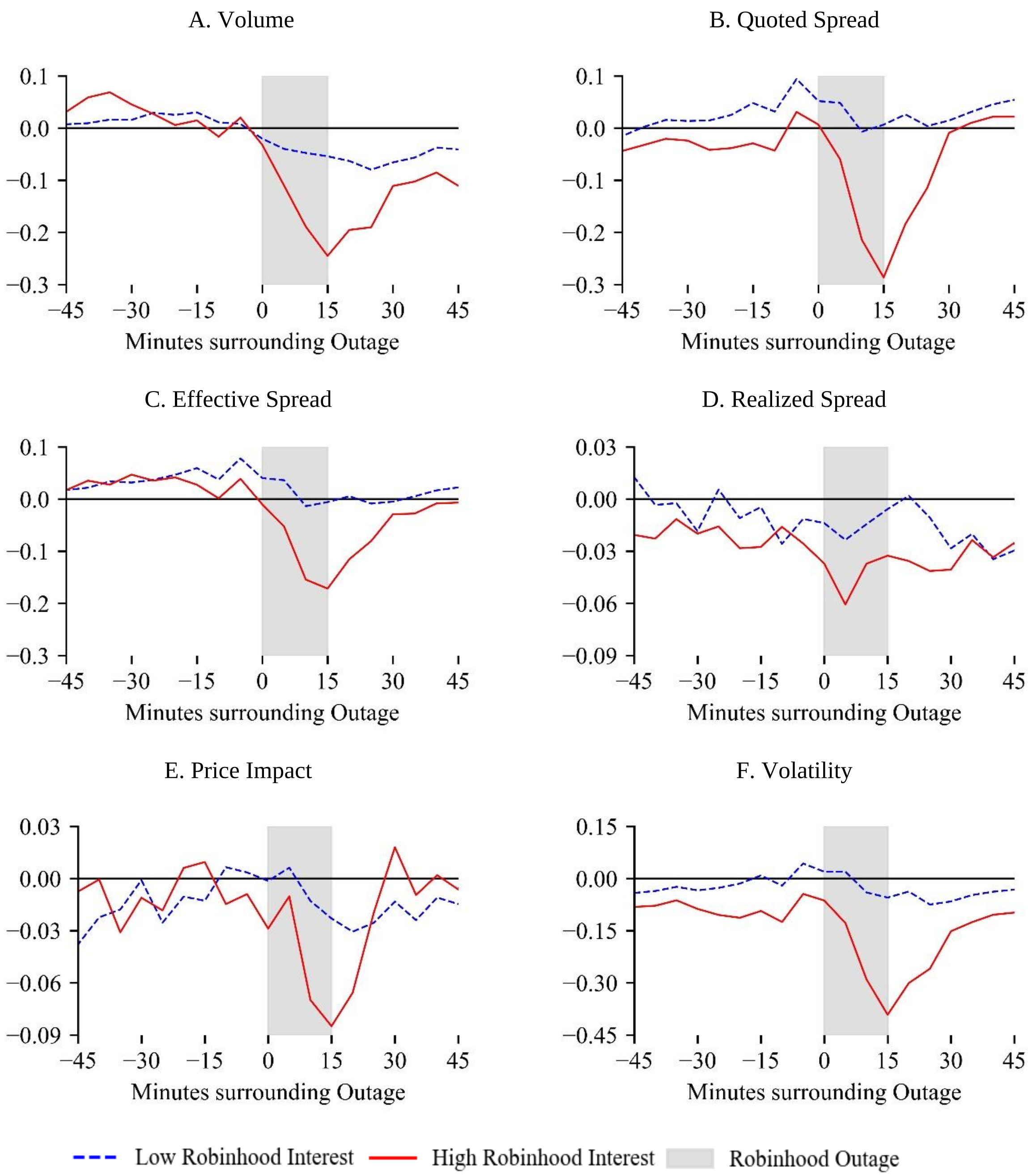

Figure 3. Market Quality Surrounding Robinhood Outages. The figure illustrates changes in market quality surrounding Robinhood platform outages. The multiple panels show alternative measures of market quality for the subsample of stocks with high interest among Robinhood investors, proxied by the number of unique WallStreetBets mentions during the control period of five trading days prior to the outage, alongside the market quality for the remaining set of sample stocks. Change in market quality in each panel is measured as the average firm's difference between market quality on the day of the outage and the time-of-day matched market quality of the control period, scaled by standard deviation of the control period. The plots consider Robinhood platform outages reported on Downdetector that last for 15 minutes and begin after 10:00 AM.

Table 1. Summary Statistics for Robinhood Holdings

The table presents descriptive statistics for stocks commonly held by Robinhood investors. The sample includes 2,015 stocks held by Robinhood investors, and the sample period is January to August 2020. We require stocks in the sample to have a daily minimum of 50 Robinhood users, a weekly average of 500 Robinhood users in the week prior to Robinhood platform outages, and have data in the CRSP, COMPUSTAT, and TAQ databases. *Robinhood Users* is the number of unique accounts that hold the stock, *WallStreetBets Mentions* is the weekly number of unique users that mention the stock in a post or comment on the Reddit forum WallStreetBets, *Trading Volume* is the daily average of trading volume, *Trading Intensity* is the daily number of trades, *Agg. Retail Volume* is the average of daily retail volume using the classification described in Boehmer et al., 2020, and *Firm Size* and *Book-to-Market* ratio represent firm characteristics from the previous fiscal quarter-end. The market quality measures *Quoted Spread*, *Effective Spread*, *Realized Spread*, and *Price Impact* are measured in basis points, *5-Minute Volatility* is the daily average of the trade-based standard deviation of returns during the 5-minute period. Proxies of high frequency trading from the NASDAQ TotalView ITCH database include *Strategic Runs*, as defined in Hasbrouck and Saar (2013), *Order Volume to Trade Volume*, and the *Cancel-Trade Ratio. Robinhood Market Maker Spreads* are the average MPID quoted spreads according to whether the firm has a payment for order flow arrangement with Robinhood. If not, then the MPID quoted spreads are part of *Other Market Maker Spreads*. *Trade Imbalance* is the dollar volume imbalance of trading activity. *Depth-Weighted Imbalance* is the imbalance of resting limit orders. *Robinhood Market Maker Depth Imbalance* (*Other Market Maker Depth Imbalance*) represent imbalances in the limit order book for Robinhood-affiliated (other) market markers.

	Mean	Std Dev	25^{th}	Median	75^{th}
Robinhood Users Holding Stock	5,252	30,930	132	474	1734
WallStreetBets Mentions from Previous Week	46.1	200.9	0.0	0.2	7.4
Trading Volume (Previous Week, Millions)	63.87	425.15	0.65	4.88	28.11
Trading Intensity (Previous Week)	2,200	4,888	156	787	2,379
Agg. Retail Volume (Previous Week, Millions)	7.68	82.45	0.06	0.31	1.62
Firm Size (Market Cap)	14,211	69,123	199	1,128	6,430
Book-to-Market Ratio	0.72	1.69	0.20	0.49	1.00
Quoted Spread (BPs)	108.21	305.72	14.68	35.70	101.84
Effective Spread (BPs)	263.99	1,435.78	8.81	22.38	74.01
Realized Spread (BPs)	135.50	924.35	1.55	6.38	44.28
Price Impact (BPs)	132.75	1,016.79	5.85	12.51	26.11
5-Minute Volatility (BPs)	364.61	1,583.08	82.01	130.64	211.11
Strategic Runs	3.30	3.06	1.43	2.71	4.41
Order Volume / Trade Volume	157.56	349.98	27.94	67.40	186.64
Cancel-Trade Ratio	13.80	11.28	5.77	12.22	18.94
Robinhood Market Maker Spreads (BPs)	329.70	984.64	112.68	125.95	140.21
Other Market Maker Spreads (BPs)	186.18	689.65	110.21	114.07	135.31
Trade Imbalance (BPs)	129.62	126.13	19.71	121.69	241.86
Depth-Weighted Imbalance (BPs)	109.43	105.06	107.13	109.86	202.64
Robinhood Market Maker Depth Imbalance (BPs)	117.02	122.85	116.17	114.17	161.50
Other Market Maker Depth Imbalance (BPs)	110.84	116.35	114.46	102.63	119.64

Table 2. Changes in Robinhood Ownership and Stock Returns

The table presents results from daily Fama-MacBeth regressions of stock returns on Robinhood ownership changes. *Robinhood Change* measures weekly changes in the number of Robinhood owners (Panel A) and percentage changes in the number of owners (Panel B). The dependent variable, Return[d,$d+\tau$] (in percent), is compounded over days d through $d+\tau$, where day d represents the day retail trading is measured. *Aggregate Retail OIB* measures weekly retail order imbalance following the methodology of Boehmer et al., 2020. Control variables include past returns, ln(*Market Cap)*, *Book-to-Market*, and one-month idiosyncratic return *Skewness* (details in Appendix A). Newey-West standard errors with lags equal to twice the horizon of the dependent variable are used. We include common stocks with a daily minimum of 50 and weekly average of 500 Robinhood users and with a stock price of at least $1 during the months of January to August 2020.

Panel A: Weekly Change in Robinhood Ownership

	Return [1,3]		Return [1,5]		Return [1,20]	
Robinhood Change	-0.042	-0.015	-0.07	-0.009	-0.075	0.253
	(-0.47)	(-0.19)	(-0.60)	(-0.08)	(-0.28)	(0.91)
Aggregate Retail OIB		0.405***		0.374***		1.047*
		(3.80)		(2.70)		(1.75)
Ret[0]		-0.047**		-0.070**		-0.052
		(-1.98)		(-1.98)		(-0.96)
Ret[-1]		-0.027		-0.056**		-0.029
		(-1.40)		(-2.10)		(-0.60)
Ret[-5,-1]		-0.031*		-0.027		-0.043
		(-1.71)		(-1.09)		(-1.00)
Market Cap[-1]		-0.108*		-0.171*		-0.683*
		(-1.92)		(-1.96)		(-1.96)
Book-to-Market		-0.203**		-0.288*		-0.731
		(-1.98)		(-1.68)		(-1.17)
Skewness		-0.021		0.004		-0.019
		(-0.60)		(0.08)		(-0.17)
Observations	299,974	243,879	299,789	243,724	298,442	242,644
Average R^2(%)	0.39	7.13	0.36	7.51	0.29	6.27

Panel B: Weekly Percentage Change in Robinhood Users

	Return [1,3]		Return [1,5]		Return [1,20]	
RH Ownership Change	-0.165	-0.199*	-0.278**	-0.306**	-0.256	-0.346
	(-1.39)	(-1.87)	(-2.01)	(-2.12)	(-1.03)	(-1.34)
Aggregate Retail OIB		0.433***		0.416***		1.094*
		(3.90)		(2.90)		(1.87)
Ret[0]		-0.04		-0.061*		-0.041
		(-1.65)		(-1.70)		(-0.73)
Ret[-1]		-0.023		-0.050*		-0.021
		(-1.17)		(-1.85)		(-0.43)
Ret[-5,-1]		-0.027		-0.021		-0.035
		(-1.45)		(-0.79)		(-0.80)
Market Cap[-1]		-0.112**		-0.176**		-0.667*
		(-2.04)		(-2.07)		(-1.96)
Book-to-Market		-0.204**		-0.290*		-0.727
		(-2.02)		(-1.73)		(-1.17)
Skewness		-0.02		0.004		-0.011
		(-0.57)		(0.08)		(-0.10)
Observations	299,968	243,878	299,783	243,723	298,436	242,643
Average R^2(%)	0.74	7.34	0.63	7.73	0.36	6.29

Table 3. Summary Statistics for Robinhood Trading Proxies

The table presents weekly summary statistics of the stock sample, partitioned into quintiles according to expected Robinhood trading activity. For each zero-commission retail trading proxy, we report the weekly summary statistics from the bottom four quintiles of the trading proxy (Q1-Q4) next to the weekly summary statistics of the top quintile (Q5). Variables are defined in Appendix A.

	WallStreetBets Mentions		Change in Robinhood Ownership	
	Q1-Q4	Q5	Q1-Q4	Q5
Stocks in Portfolio	1647	302.9	1560.8	389.1
WallStreetBets Mentions	2.4	814.9	14.7	591.7
Change in Robinhood Ownership	7.4	114.8	4.4	103.0
Change in Robinhood Ownership (%)	5.1	4.9	3.7	10.7
Robinhood Users Holding Stock	2,114.5	45,093	1,816.7	35,909.4
Trading Volume (Previous Week, Millions)	38.8	440.1	39.8	346
Trading Intensity (Previous Week)	2,120	9,282	2,133.6	7,640.7
Agg. Retail Volume (Previous Week, Millions)	2.5	68.2	2.3	53.6
Firm Size (Market Capitalization)	15,261.0	93,187.2	18,107.8	84,262.1
Book-to-Market Ratio	0.7	0.5	0.6	0.6
Quoted Spread (BPs)	72	20.2	71	34.7
Effective Spread (BPs)	160.3	127.2	156.9	145.6
Realized Spread (BPs)	86.1	106	85.9	100.2
Price Impact (BPs)	76.6	60.8	73.3	76.1
5-Minute Volatility (BPs)	185.3	239.7	181.5	255
Strategic Runs	1.7	3	1.7	2.8
Order Volume / Trade Volume	102.1	129.1	101	133
Cancel-Trade Ratio	10.4	17	13.7	15.1
Robinhood Market Maker Spreads (BPs)	164	46.7	131.3	50.6
Other Market Maker Spreads (BPs)	86	32.6	65.2	44.1
Trade Imbalance (BPs)	31.5	45.1	31.4	38.5
Depth-Weighted Imbalance (BPs)	109.3	130.3	99.4	197.6
Robinhood Market Maker Depth Imbalance (BPs)	108.9	121.9	101.6	132.8
Other Market Maker Depth Imbalance (BPs)	103.6	96.7	94.3	89.7

Table 4. Robinhood Platform Outages and Trading Activity

The table reports the effects of Robinhood outages on trading activity for stocks with high Robinhood interest as in Equation 2 in the text. The sample consists of 5-minute intervals, t, for each firm i during the window on day d when the Robinhood platform experiences an outage, matched with 5-minute intervals for the same stock and time of day for each of the 5 trading days preceding the outage date. The first three specifications report estimates for actual Robinhood outages, the remaining specifications present estimates for pseudo outages, where observations are shifted by one hour from the end of the actual outage event. The dependent variables include the natural log of trading volume, the natural log of the number of trades, and the natural log of aggregate retail volume. The Robinhood outage is indicated by the indictor variable $Outage_t$. The variable, $RH_{i,d-1}$, is equal to one for stocks in the top quintile of Robinhood interest and zero otherwise. We consider two proxies for Robinhood interest, WallStreetBets Mentions (Panel A) and Robinhood Ownership Change (Panel B), both measured over the previous five days. The t-statistics from standard errors double clustered at the firm and day level are reported in parentheses, where 1%, 5%, and 10% significance levels are marked by ***, **, and * respectively. Δ R-squared values are incremental after fixed effects. See Appendix A for further details on variable definitions.

Panel A: WallStreetBets Mentions as the Proxy for Expected Robinhood Trading

	Robinhood Event Outages			Pseudo Outages		
	Trading Volume	Trading Intensity	Agg. Retail Volume	Trading Volume	Trading Intensity	Agg. Retail Volume
$RH_{i,d-1} \times Outage_t$	-0.084**	-0.062*	-0.024	0.010	0.024	0.078
	(-2.260)	(-1.944)	(-0.332)	(0.372)	(0.895)	(1.610)
$RH_{i,d-1}$	0.335***	0.221***	0.503***	0.371***	0.334***	0.521***
	(8.067)	(6.951)	(9.544)	(8.765)	(7.814)	(10.327)
$Outage_t$	0.158	0.047	0.188	-0.041	-0.036	-0.028
	(1.301)	(0.342)	(1.432)	(-0.485)	(-0.439)	(-0.467)
Fixed Effects	Firm, Day	Firm, Day	Firm, Day	Firm, Day	Firm, Day	Firm, Day
Observations	2,277,649	2,277,649	2,277,649	1,823,321	1,823,321	1,823,321
Firm Clusters	2,015	2,015	2,015	2,001	2,001	2,001
Δ R-squared (%)	0.6423	0.2613	0.4908	0.8600	0.2242	0.6015

Panel B: Changes in Robinhood Ownership as the Proxy for Expected Robinhood Trading

	Robinhood Event Outages			Pseudo Outages		
	Trading Volume	Trading Intensity	Agg. Retail Volume	Trading Volume	Trading Intensity	Agg. Retail Volume
$RH_{i,d-1} \times Outage_t$	-0.117**	-0.077**	-0.082	-0.055	0.021	0.021
	(-2.296)	(-1.993)	(-1.06)	(-1.371)	(0.744)	(0.391)
$RH_{i,d-1}$	0.543***	0.415***	0.851***	0.558***	0.46***	0.764***
	(13.866)	(15.296)	(17.679)	(15.724)	(12.779)	(17.483)
$Outage_t$	0.165	0.051	0.199	-0.027	-0.035	-0.016
	(1.334)	(0.36)	(1.499)	(-0.321)	(-0.425)	(-0.265)
Fixed Effects	Firm, Day	Firm, Day	Firm, Day	Firm, Day	Firm, Day	Firm, Day
Observations	2,277,649	2,277,649	2,277,649	1,823,321	1,823,321	1,823,321
Firm Clusters	2,015	2,015	2,015	2,001	2,001	2,001
Δ R-squared (%)	2.2381	1.2991	1.8685	2.658	0.6056	1.7571

Table 5. Robinhood Platform Outages and Stock Liquidity

The table reports the effects of Robinhood outages on measures of stock liquidity for stocks with high Robinhood interest as in Equation (3). The sample consists of 5-minute intervals, *t*, for each firm *i* during the window on day *d* when the Robinhood platform experiences an outage, matched with 5-minute intervals for the same stock and time for each of the 5 trading days preceding the outage date. The Robinhood Outages sample is the actual time window of the outage, along with the time-of-day matched control period. The Pseudo outage is the time window one hour following the conclusion of the platform outage with the corresponding control period. The dependent variable is a measure of liquidity during the 5-minute window, where the measures include the *Quoted Spread*, *Effective Spread*, *Realized Spread*, and *Price Impact*, all expressed in basis points. The independent variables are as described in Table 4 and Section 5, where Panels A, and B reports results for two different proxies of expected Robinhood Trading. Each model specification includes firm and day fixed effects, and Δ R-squared values are incremental after fixed effects. *t*-statistics from standard errors double clustered at the firm and day level are reported in parentheses, where 1%, 5%, and 10% significance levels are marked by ***, **, and * respectively.

	Robinhood Outages				Pseudo Outages			
	Quoted Spread	Effective Spread	Realized Spread	Price Impact	Quoted Spread	Effective Spread	Realized Spread	Price Impact
Panel A: WallStreetBets Activity as the Proxy for Expected Robinhood Trading								
$RH_{i,d-1} \times Outage_t$	-2.927**	-6.11*	-4.744*	-5.069**	-0.726	0.558	2.306	-2.524
	(-2.075)	(-1.862)	(-1.752)	(-2.04)	(-0.644)	(0.171)	(1.076)	(-1.211)
$RH_{i,d-1}$	-1.965***	-9.225	-12.297**	-2.156	-1.645***	-5.067	-4.837	-1.688
	(-2.906)	(-1.359)	(-2.03)	(-0.611)	(-2.824)	(-0.851)	(-1.371)	(-0.518)
$Outage_t$	4.546	6.601	0.331	4.211	0.704	-0.566	-0.778	0.758
	(0.864)	(0.934)	(0.072)	(1.083)	(0.984)	(-0.415)	(-0.509)	(0.852)
Firm Clusters	2,015	2,015	2,015	2,015	2,001	2,001	2,001	2,001
Δ R-Squared (%)	0.109	0.0077	0.0104	0.0023	0.0524	0.0018	0.0016	0.0009
Panel B: Changes in Robinhood Ownership as the Proxy for Expected Robinhood Trading								
$RH_{i,d-1} \times Outage_t$	-2.841**	-6.007*	-8.763***	-7.928***	-0.799	0.441	1.307	-1.787
	(-2.399)	(-1.876)	(-3.429)	(-2.683)	(-0.865)	(0.184)	(0.756)	(-1.102)
$RH_{i,d-1}$	-3.391***	2.988	-0.363	4.494	-2.35***	-3.333	-3.902	-0.494
	(-5.004)	(0.529)	(-0.117)	(1.269)	(-5.393)	(-0.87)	(-1.302)	(-0.233)
$Outage_t$	4.547	6.626	1.158	4.803	0.72	-0.556	-0.612	0.636
	(0.874)	(0.93)	(0.251)	(1.232)	(1.028)	(-0.432)	(-0.399)	(0.781)
Firm Clusters	2,015	2,015	2,015	2,015	2,001	2,001	2,001	2,001
Δ R-Squared (%)	0.1955	0.0021	0.0028	0.0041	0.1336	0.0011	0.0015	0.0003

Table 6. Robinhood Platform Outages and Stock Return Volatility

The table reports the effects of Robinhood outages on a measure of stock return volatility for stocks with high Robinhood interest (see Eq. (4)). The sample consists of 5-minute intervals, t, for each firm i during the window on day d when the Robinhood platform experiences an outage, matched with 5-minute intervals for the same stock and time for each of the 5 trading days preceding the outage date. The Robinhood Outage sample is the actual time window in which the Robinhood platform was down, along with the time-of-day matched control period. The Pseudo outage is the time window one hour following the conclusion of the platform outage along the time-of-day matched control period which is also shifted by one hour. The dependent variable is the volatility of returns during the 5-minute window, expressed in basis points. The independent variables are as described in Table 4 and Section 5. Panels A and B reports the results for two different proxies for expected Robinhood Trading. Each model specification includes firm and day fixed effects, and Δ R-squares are incremental after fixed effects. t-Statistics from standard errors double clustered at the firm and day level are reported in parentheses, where significance at the 1%, 5%, and 10% levels are marked on the coefficients by ***, **, and * respectively.

Panel A: WallStreetBets Activity as the Proxy for Expected Robinhood Trading

	Robinhood Outage	Pseudo Event
$RH_{i,d-1} \times Outage_t$	-16.982**	-1.615
	(-2.055)	(-1.077)
$RH_{i,d-1}$	-28.045**	-1.839
	(-1.962)	(-0.591)
$Outage_t$	2.516	2.293
	(0.499)	(0.705)
Firm Clusters	2,015	2,001
Δ R-Squared (%)	0.0181	0.0009

Panel B: Changes in Robinhood Ownership as the Proxy for Expected Robinhood Trading

	Robinhood Outage	Pseudo Event
$RH_{i,d-1} \times Outage_t$	-17.572**	-1.033
	(-2.161)	(-1.200)
$RH_{i,d-1}$	9.728	0.597
	(0.823)	(0.267)
$Outage_t$	2.762	3.372
	(0.516)	(1.051)
Firm Clusters	2,015	2,001
Δ R-Squared (%)	0.0037	0.0002

Table 7. Robinhood Platform Outages and Market Quality – Robustness Checks

The table reports robustness checks of the results in Tables 4-6. For brevity, each panel reports only the interaction term that captures the effects of outages on stocks with high expected Robinhood trading (full regression results are reported in Internet Appendix Table IA4). RH_{d-1}^{WSB} denotes the specifications in which high expected Robinhood trading is proxied using lagged WallStreetBets mentions, and $RH_{d-1}^{\Delta RH}$ refers to specifications using lagged Robinhood trading as the proxy. Panel A reports the results from estimates obtained after excluding stocks identified as having an increase of at least 20% in WallStreetBets Mentions (WSB) on the outage date. Panel B reports results after excluding outages that begin prior to 9:45 AM EST. Panel C excludes outages in March of 2020. Panel D limits the outage window duration to match the length of the pseudo window. Panel E reports the effects from a 5-day benchmark beginning 10 days before the outage event. Panel F requires stocks to be owned by 1000 Robinhood investors.

	Trading Volume (Log)	Trading Intensity (Log)	Quoted Spread (BPs)	Effective Spread (BPs)	Realized Spread (BPs)	Price Impact (BPs)	Return Volatility (BPs)
Panel A: Exclude Firm-Outage Events with a 20% Spike in WallStreetBets Mentions							
$RH_{i,d-1}^{WSB} \times Outage_t$	-0.102***	-0.074**	-2.958**	-6.391*	-5.186*	-5.573**	-9.977**
	(-2.794)	(-2.326)	(-2.051)	(-1.843)	(-1.65)	(-2.065)	(-2.375)
$RH_{i,d-1}^{\Delta RH} \times Outage_t$	-0.133***	-0.095**	-2.83**	-6.591**	-9.312***	-8.784***	-11.72**
	(-2.622)	(-2.418)	(-2.36)	(-1.982)	(-3.507)	(-2.849)	(-2.361)
Panel B: Exclude Platform Outages that begin before 9:45 AM							
$RH_{i,d-1}^{WSB} \times Outage_t$	-0.087**	-0.067**	-2.86**	-5.936*	-5.103*	-4.876*	-16.566**
	(-2.294)	(-2.123)	(-2.02)	(-1.789)	(-1.842)	(-1.954)	(-2.025)
$RH_{i,d-1}^{\Delta RH} \times Outage_t$	-0.122**	-0.085**	-2.789**	-5.886*	-8.856***	-7.976***	-17.704**
	(-2.379)	(-2.273)	(-2.347)	(-1.8)	(-3.43)	(-2.665)	(-2.158)
Panel C: Exclude All Platform Outages in March 2020							
$RH_{i,d-1}^{WSB} \times Outage_t$	-0.061*	-0.040	-5.873*	-5.567*	-2.906	-6.225**	-19.950**
	(-1.663)	(-0.717)	(-1.831)	(-1.744)	(-1.322)	(-2.241)	(-2.263)
$RH_{i,d-1}^{\Delta RH} \times Outage_t$	-0.105**	-0.142**	-1.035	-5.235**	-5.543**	-1.853	-2.247
	(-2.461)	(-1.996)	(-0.817)	(-2.321)	(-2.122)	(-0.826)	(-0.800)
Panel D: Match Platform Outage Event Windows More Closely to Pseudo Windows							
$RH_{i,d-1}^{WSB} \times Outage_t$	-0.077**	-0.038*	-3.107**	-9.843**	-4.252*	-4.995**	-3.788*
	(-2.025)	(-1.696)	(-2.311)	(-2.346)	(-1.674)	(-1.96)	(-1.647)
$RH_{i,d-1}^{\Delta RH} \times Outage_t$	-0.056**	-0.077**	-3.736***	-5.191*	-3.075*	-5.811***	-9.132***
	(-2.059)	(-2.025)	(-3.152)	(-1.771)	(-1.851)	(-2.712)	(-3.427)
Panel E: Measure Benchmark Control Period -6 to -10 Days before Platform Outage (Instead of -1 to -5)							
$RH_{i,d-1}^{WSB} \times Outage_t$	-0.116**	-0.159***	-2.684*	-12.101**	-8.357**	-6.96**	-15.502**
	(-2.199)	(-3.544)	(-1.867)	(-2.411)	(-2.401)	(-2.227)	(-2.162)
$RH_{i,d-1}^{\Delta RH} \times Outage_t$	-0.122**	-0.136**	-3.287***	-8.666**	-8.431***	-7.146**	-13.822**
	(-1.985)	(-2.439)	(-2.894)	(-2.341)	(-2.739)	(-2.532)	(-2.35)
Panel F: Require an Average of 1000 Robinhood Owners Prior to the Outage							
$RH_{i,d-1}^{WSB} \times Outage_t$	-0.044*	-0.052**	-3.361**	-14.026*	-5.864*	-2.224*	-2.838**
	(1.769)	(-2.179)	(-2.268)	(-1.759)	(-1.795)	(-1.775)	(-2.074)
$RH_{i,d-1}^{\Delta RH} \times Outage_t$	-0.061**	-0.019*	-4.163***	-11.765**	-7.158	-5.076*	-8.389*
	(-2.231)	(-1.745)	(-3.427)	(-2.351)	(-1.020)	(-1.829)	(-1.698)

Table 8. Robinhood Platform Outages and High Frequency Trading Activity

The table reports the effects of Robinhood outages on measures of HFT activity for stocks with high Robinhood interest (see Eq. (5)). The dependent variables represent alternative proxies of high frequency trading: the natural log of Strategic Runs from Hasbrouck and Saar (2013), the natural log of order volume scaled by trade volume, and the natural log of the Cancel-to-Trade ratio. The independent variables are as described in Table 4. Panels A and B report results for two proxies of expected Robinhood Trading. The sample consists of 5-minute intervals, t, for each firm i during the window on day d when the Robinhood platform experiences an outage, matched with 5-minute intervals for the same stock and time for each of the 5 trading days preceding the outage date. The Robinhood Event Outages sample is the actual time window in which the Robinhood platform experienced an outage along with the time-of-day matched control period. The Pseudo Outage is the time window one hour following the conclusion of the platform outage along with the time-of-day matched control period. Each model specification includes firm and day fixed effects, and Δ R-squares are incremental after fixed effects. t-Statistics from standard errors double clustered at the firm and day level are reported in parentheses, where significance at the 1%, 5%, and 10% levels are marked on the coefficients by ***, **, and * respectively.

Panel A: WallStreetBets Activity as the Proxy for Expected Robinhood Trading

	Robinhood Event Outages			Pseudo Outages		
	Strategic Runs	Order Vol / Trade Vol	Cancel-Trade Ratio	Strategic Runs	Order Vol / Trade Vol	Cancel-Trade Ratio
$RH_{i,d\text{-}1} \times Outage_t$	-0.064**	-0.08***	-0.058***	-0.001	-0.025	-0.028
	(-1.961)	(-2.884)	(-2.666)	(-0.047)	(-0.643)	(-1.251)
$RH_{i,d\text{-}1}$	0.124***	0.084***	0.053***	0.185***	0.122***	0.052***
	(5.834)	(4.283)	(3.609)	(7.686)	(4.341)	(3.355)
$Outage_t$	-0.205	-0.001	-0.099	-0.031	0.045	0.043
	(-1.109)	(-0.011)	(-1.242)	(-1.397)	(1.150)	(1.125)
Firm Clusters	2,015	2,015	2,015	2,001	2,001	2,001
Δ R-squared (%)	0.14505	0.0280	0.0838	0.1531	0.0221	0.0319

Panel B: Changes in Robinhood Ownership as the Proxy for Expected Robinhood Trading

	Robinhood Event Outages			Pseudo Outages		
	Strategic Runs	Order Vol / Trade Vol	Cancel-Trade Ratio	Strategic Runs	Order Vol / Trade Vol	Cancel-Trade Ratio
$RH_{i,d\text{-}1} \times Outage_t$	-0.079**	-0.051**	-0.041**	-0.038*	-0.005	0.003
	(-2.493)	(-2.282)	(-2.144)	(-1.696)	(-0.161)	(0.136)
$RH_{i,d\text{-}1}$	0.176***	0.052***	0.026*	0.265***	0.175***	0.032*
	(7.671)	(3.157)	(1.897)	(10.205)	(5.460)	(1.882)
$Outage_t$	-0.202	-0.007	-0.102	-0.024	0.042	0.037
	(-1.096)	(-0.054)	(-1.274)	(-1.061)	(1.085)	(0.970)
Firm Clusters	2,015	2,015	2,015	2,001	2,001	2,001
Δ R-squared (%)	0.2400	0.0138	0.0648	0.3856	0.0592	0.0233

Table 9. Robinhood Outages and Quoting by HFTs with Order Flow Arrangements with Robinhood

The table reports the effects of Robinhood outages on the aggressiveness of market makers quotes for stocks with high Robinhood interest. The dependent variable is the average distance between the best bid and best offer of market makers identified by MPID affiliated quotes in the NASDAQ TotalView ITCH data, partitioned according to market makers with payment for order flow arrangements with Robinhood. Market maker spreads are expressed as a percentage of stock price and quoted in basis points. The independent variables are as described in Table 4, where Panels A and B report results for two different proxies of expected Robinhood Trading. The sample consists of 5-minute intervals, t, for each firm i during the window on day d when the Robinhood platform experiences an outage, matched with 5-minute intervals for the same stock and time for each of the 5 trading days preceding the outage date. The Robinhood Outage sample is the actual time window in which the Robinhood platform experienced an outage along with the time-of-day matched control period. The Pseudo outage is the time window one hour following the conclusion of the platform outage along the time-of-day matched control period which is also shifted by one hour. Each model specification includes firm and day fixed effects, and Δ R-squares are incremental after fixed effects. t-Statistics from standard errors double clustered at the firm and day level are reported in parentheses, where significance at the 1%, 5%, and 10% levels are marked on the coefficients by ***, **, and * respectively.

Panel A: WallStreetBets Activity as the Proxy for Expected Robinhood Trading

	Robinhood Outages		Pseudo Outages	
	Robinhood Market Maker Spreads	Other Market Maker Spreads	Robinhood Market Maker Spreads	Other Market Maker Spreads
$RH_{i,d-1} \times Outage_t$	-10.957***	7.025	1.872	4.456
	(-2.809)	(1.06)	(0.425)	(0.204)
$RH_{i,d-1}$	3.510*	2.209	3.287*	-1.160
	(1.792)	(0.123)	(1.864)	(-1.091)
$Outage_t$	-1.070	5.725	2.842	1.313
	(-0.08)	(0.134)	(2.271)	(0.711)
Firm Clusters	2,015	2,015	2,001	2,001
Δ R-squared (%)	0.0289	0.0422	0.0572	0.0622

Panel B: Changes in Robinhood Ownership as the Proxy for Expected Robinhood Trading

	Robinhood Outages		Pseudo Outages	
	Robinhood Market Maker Spreads	Other Market Maker Spreads	Robinhood Market Maker Spreads	Other Market Maker Spreads
$RH_{i,d-1} \times Outage_t$	-10.885***	3.912	-0.761	3.881
	(-3.591)	(1.234)	(-0.335)	(0.051)
$RH_{i,d-1}$	10.523*	7.918*	3.043	2.953
	(1.755)	(1.908)	(1.532)	(1.428)
$Outage_t$	-1.090	5.028	9.176	0.808
	(-0.083)	(1.166)	(1.397)	(0.427)
Firm Clusters	2,015	2,015	2,001	2,001
Δ R-squared (%)	0.1248	0.0717	0.1376	0.0822

Table 10. Robinhood Platform Outages and Trade and Depth Order Imbalances

The table reports the effects of Robinhood outages on inventory imbalance for stocks with high Robinhood interest. The dependent variable in each specification is a measure of trade or depth imbalance. Trade imbalance is the absolute difference between the dollar volume of buy and sell trades, expressed as a percent of all dollar volume traded and reported in basis points. Depth-weighted imbalance is the absolute difference between the depth-weighted limit buy order price distance from the quoted midpoint and the depth-weighted limit sell order distance from the quoted midpoint, scaled by the quoted midpoint and reported in basis points. The market maker depth imbalance measures are the depth-weighted imbalance for the subset of orders with MPID attributions, partitioned by market makers with and without Robinhood payment for order flow arrangements. The sample consists of 5-minute intervals, t, for each firm i during the window on day d when the Robinhood platform experiences an outage, matched with 5-minute intervals for the same stock and time for each of the 5 trading days preceding the outage date. The Robinhood Outage sample is the actual time window in which the Robinhood platform experienced an outage along with the time-of-day matched control period. The Pseudo Outage is the time window one hour following the conclusion of the platform outage along the time-of-day matched control period which is also shifted by one hour. The independent variables are as described in Table 4, where Panel A and B reports results for two different proxies of expected Robinhood Trading. Each model specification includes firm and day fixed effects, and Δ R-squares are incremental after fixed effects. t-Statistics from standard errors double clustered at the firm and day level are reported in parentheses, where significance at the 1%, 5%, and 10% levels are marked on the coefficients by ***, **, and * respectively.

Panel A: WallStreetBets Activity as the Proxy for Expected Robinhood Trading

	Robinhood Outages				Pseudo Outages			
	Trade Imbalance	Depth Weighted Imbalance	Robinhood Market Maker Depth Imbal.	Other Market Maker Depth Imbalance	Trade Imbalance	Depth Weighted Imbalance	Robinhood Market Maker Depth Imbal.	Other Market Maker Depth Imbalance
$RH_{i,d-1} \times Outage_t$	-10.151**	-58.307***	-10.135**	-13.228	-5.275	19.753	6.219	-18.808
	(-2.54)	(-3.456)	(-2.523)	(-0.727)	(-1.333)	(1.111)	(1.186)	(-1.008)
$RH_{i,d-1}$	13.437***	56.202***	5.275*	-1.463	13.391***	66.996***	-1.658	6.699
	(2.801)	(4.267)	(1.712)	(-0.109)	(2.950)	(5.582)	(-0.51)	(0.398)
$Outage_t$	-10.783	-8.242	-34.434	21.809	1.061	-13.559	-3.079	5.378
	(-1.115)	(-0.500)	(-1.125)	(0.982)	(0.173)	(-1.31)	(-1.179)	(0.385)
Firm Clusters	2,015	2,015	2,015	2,015	2,001	2,001	2,001	2,001
Δ R-Squared (%)	0.0141	0.1637	0.0169	0.0014	0.0091	0.2292	0.0012	0.0011

Table 10. Robinhood Platform Outages and Trade and Depth Order Imbalances (continued)

Panel B: Changes in Robinhood Ownership as the Proxy for Expected Robinhood Trading

	Robinhood Outages				Pseudo Outages			
	Trade Imbalance	Depth Weighted Imbalance	Robinhood Market Maker Depth Imbal.	Other Market Maker Depth Imbalance	Trade Imbalance	Depth Imbalance	Robinhood Market Maker Depth Imbal.	Other Market Maker Depth Imbalance
$RH_{i,d-1} \times Outage_t$	-13.265**	-41.938**	-16.081***	-2.298	-1.486	18.649	0.836	-13.692
	(-2.506)	(-2.547)	(-3.692)	(-0.134)	(-0.307)	(1.338)	(0.202)	(-0.753)
$RH_{i,d-1}$	3.201	70.443***	3.682	44.44	1.126	72.821***	6.326**	38.419
	(0.756)	(2.709)	(1.054)	(1.399)	(0.279)	(3.353)	(2.327)	(1.183)
$Outage_t$	-10.113	-11.449	-33.186	19.797	0.306	-13.154	-1.953	4.295
	(-1.054)	(-0.697)	(-1.069)	(0.926)	(0.051)	(-1.361)	(-0.777)	(0.314)
Firm Clusters	2,015	2,015	2,015	2,015	2,001	2,001	2,001	2,001
Δ R-Squared (%)	0.0122	0.2556	0.0181	0.0138	0.0001	0.3561	0.0029	0.0133

Table 11. Robinhood Platform Outages and Robinhood Inventory Risk

The table reports the effects of inventory risk and Robinhood outages on measures of stock liquidity for stocks with high Robinhood interest. The dependent variable in the first four specifications represent measures of market quality, while the latter four specifications represent measures of inventory imbalance. The variable $InventoryRisk_{i,d-1}$ identifies stocks in the highest quintile according to autocorrelation in Robinhood investor hourly changes in positions during the 5-day pre-event window. The sample consists of 5-minute intervals, *t*, for each firm *i* during the window on day *d* when the Robinhood platform experiences an outage, matched with 5-minute intervals for the same stock and time for each of the 5 trading days preceding the outage date. Panels A and B represent the two proxies of expected Robinhood trading. See Appendix A for further details on variable definitions. All specifications include firm and day fixed effects, and Δ R-squares are incremental after fixed effects. *t*-Statistics from standard errors double clustered at the firm and day level are reported in parentheses, where significance at the 1%, 5%, and 10% levels are marked on the coefficients by ***, **, and * respectively.

Panel A: WallStreetBets Activity as the Proxy for Expected Robinhood Trading

	Quoted Spread	Effective Spread	Realized Spread	Price Impact	Trade Imbalance	Depth Weighted Imbalance	Robinhood MM Depth Imbalance	Robinhood MM Quoted Spread
$RH_{i,d-1}$ × $InventoryRisk_{i,d-1}$ × $Outage_t$	-2.902**	-46.488*	-35.73**	-18.824**	-4.246**	-19.54**	-6.326**	-5.613*
	(-2.241)	(-1.947)	(-2.163)	(-2.009)	(2.486)	(-2.069)	(-2.149)	(-1.824)
$RH_{i,d-1}$ × $Outage_t$	-3.201**	-9.364	-5.681	3.113	-11.530***	-58.51***	-11.134**	-13.477***
	(-2.103)	(-1.058)	(-1.227)	(0.604)	(-2.641)	(-2.913)	(-2.339)	(-2.793)
$Outage_t$ × $InventoryRisk_{i,d-1}$	1.458*	8.515	4.844	4.123	-1.489	3.981	-6.286	1.438
	(1.658)	(1.364)	(0.678)	(0.8)	(-0.4)	(0.29)	(-1.319)	(0.28)
$RH_{i,d-1}$ × $InventoryRisk_{i,d-1}$	0.021	29.639	20.904	6.627	0.8381	-3.649	-2.527	3.823
	(0.026)	(1.46)	(1.314)	(1.087)	(0.216)	(-0.32)	(-0.51)	(1.367)
$RH_{i,d-1}$	-1.583**	-16.346**	-2.056	-12.699**	13.241***	57.036***	4.739	-4.171
	(-2.132)	(-2.162)	(-0.34)	(-2.014)	(2.796)	(4.387)	-1.413	(-1.513)
$Outage_t$	5.347	2.177	6.623	-8.174	-10.493	-8.867	-33.441	-1.449
	(0.94)	(0.28)	(0.713)	(-1.043)	(-1.085)	(-0.51)	(-1.089)	(-0.102)
$InventoryRisk_{i,d-1}$	0.912**	0.879	-1.269	3.674	-0.590	4.345	0.594	-7.286***
	(2.422)	(0.331)	(-0.314)	(1.347)	(-0.281)	(0.613)	(0.194)	(-2.757)
Firm Clusters	2,015	2,015	2,015	2,015	2,015	2,015	2,015	2,015
Δ R-squared (%)	0.0588	0.0041	0.0005	0.0009	0.0143	0.1663	0.0174	0.0627

Table 11. Robinhood Platform Outages and Robinhood Inventory Risk (continued)

Panel B: Changes in Robinhood Ownership as the Proxy for Expected Robinhood Trading

	Quoted Spread	Effective Spread	Realized Spread	Price Impact	Trade Imbalance	Depth Weighted Imbalance	Robinhood MM Depth Imbalance	Robinhood MM Quoted Spread
$RH_{i,d-1}$ × $InventoryRisk_{i,d-1}$ × $Outage_t$	-1.321**	-1.929**	-1.575*	-2.814*	-2.718**	-21.166***	-4.370***	-3.420*
	(-2.144)	(-2.125)	(-1.755)	(-1.897)	(-2.392)	(-2.785)	(-2.762)	(-1.762)
$RH_{i,d-1}$ × $Outage_t$	-4.734***	-8.983	-8.684	-8.094	-13.995**	-48.398***	-16.872***	-12.559***
	(-3.796)	(-1.612)	(-1.157)	(-1.354)	(-2.265)	(-2.698)	(-3.232)	(-3.283)
$Outage_t$ × $InventoryRisk_{i,d-1}$	1.082	5.818	1.55	1.12	-1.224	-4.798	-5.015	0.955
	(1.31)	(1.24)	(0.205)	(0.195)	(-0.395)	(-0.328)	(-1.036)	(0.201)
$RH_{i,d-1}$ × $InventoryRisk_{i,d-1}$	-1.021	-4.996	-10.757	3.256	-1.021	-5.599	0.041	5.742
	(-0.878)	(-0.521)	(-1.412)	(0.427)	(-0.256)	(-0.471)	(0.009)	(1.514)
$RH_{i,d-1}$	-3.255***	-12.21	-15.77**	2.241	-2.899	72.064***	3.523	-16.146***
	(-4.25)	(-1.256)	(-2.188)	(0.349)	(-0.67)	(5.601)	(0.928)	(-5.053)
$Outage_t$	5.696	1.876	6.996	-5.634	-9.906	-10.582	-32.331	-1.338
	(1.015)	(0.229)	(0.71)	(-0.687)	(-1.03)	(-0.616)	(-1.046)	(-0.096)
$InventoryRisk_{i,d-1}$	0.911***	3.342	0.671	4.496*	0.235	4.186	-0.623	-7.722***
	(2.606)	(0.857)	(0.153)	(1.719)	(0.119)	(0.632)	(-0.218)	(-2.811)
Firm Clusters	2,015	2,015	2,015	2,015	2,015	2,015	2,015	2,015
Δ R-squared (%)	0.1089	0.0028	0.0017	0.0005	0.0123	0.2586	0.0185	0.1617

Internet Appendix

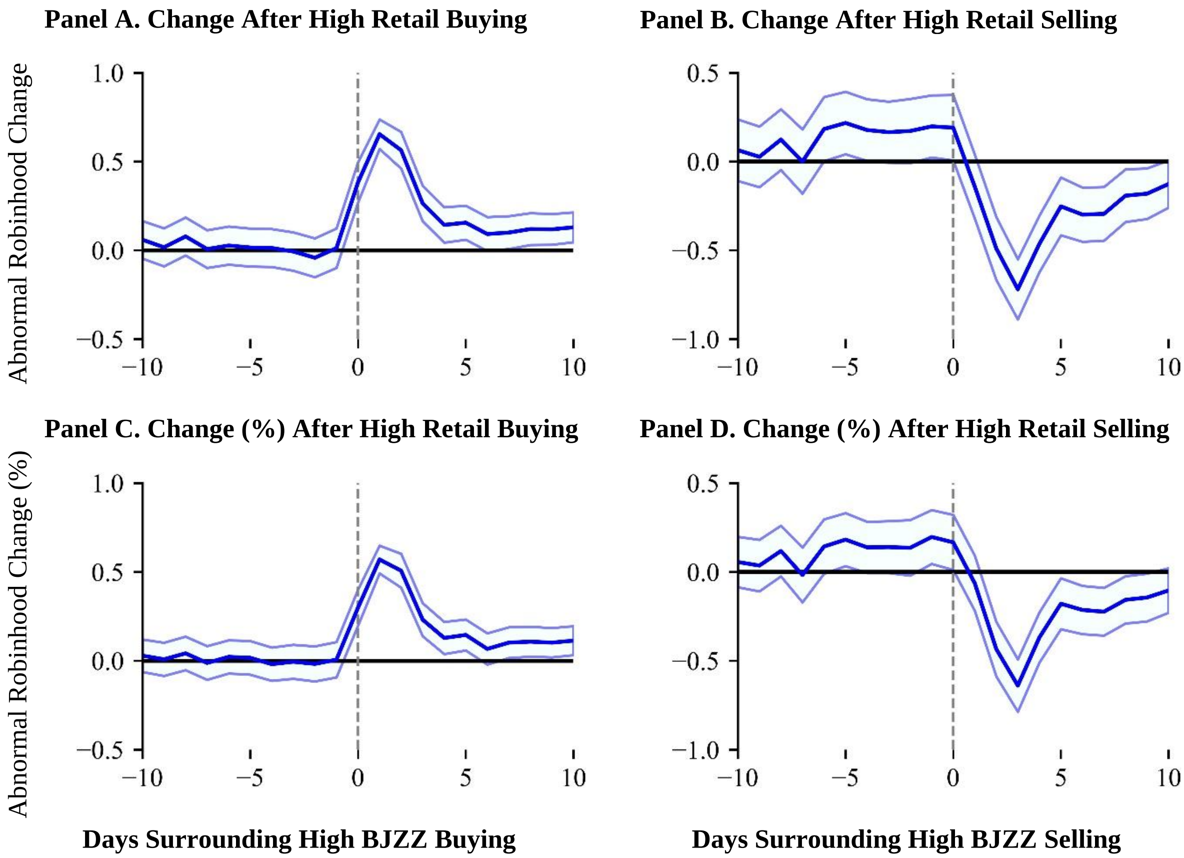

Figure IA1. Robinhood Activity Surrounding High Buying and Selling Days among all Retail Traders. High retail buying and selling days are defined on day 0 as being in the top and bottom quintile of stocks, respectively, according to signed daily retail dollar volume using the retail classification described in Boehmer et al., 2020. Abnormal activity on days -10 to +10 are estimated relative to a 20-day moving average benchmark from day -30 to -11, scaled by the standard deviation of the 20-day benchmark period. Estimates of abnormal activity are indicated by the solid blue line and are obtained from ordinary least squares regressions to remove firm fixed effects, where the shaded area surrounding the blue line indicates the 99% confidence interval. *Abnormal Robinhood Change* is the increase or decrease in aggregate changes in hourly Robinhood positions relative to the benchmark, *Abnormal Robinhood Change (%)* is equivalent measure scaled by total Robinhood users.

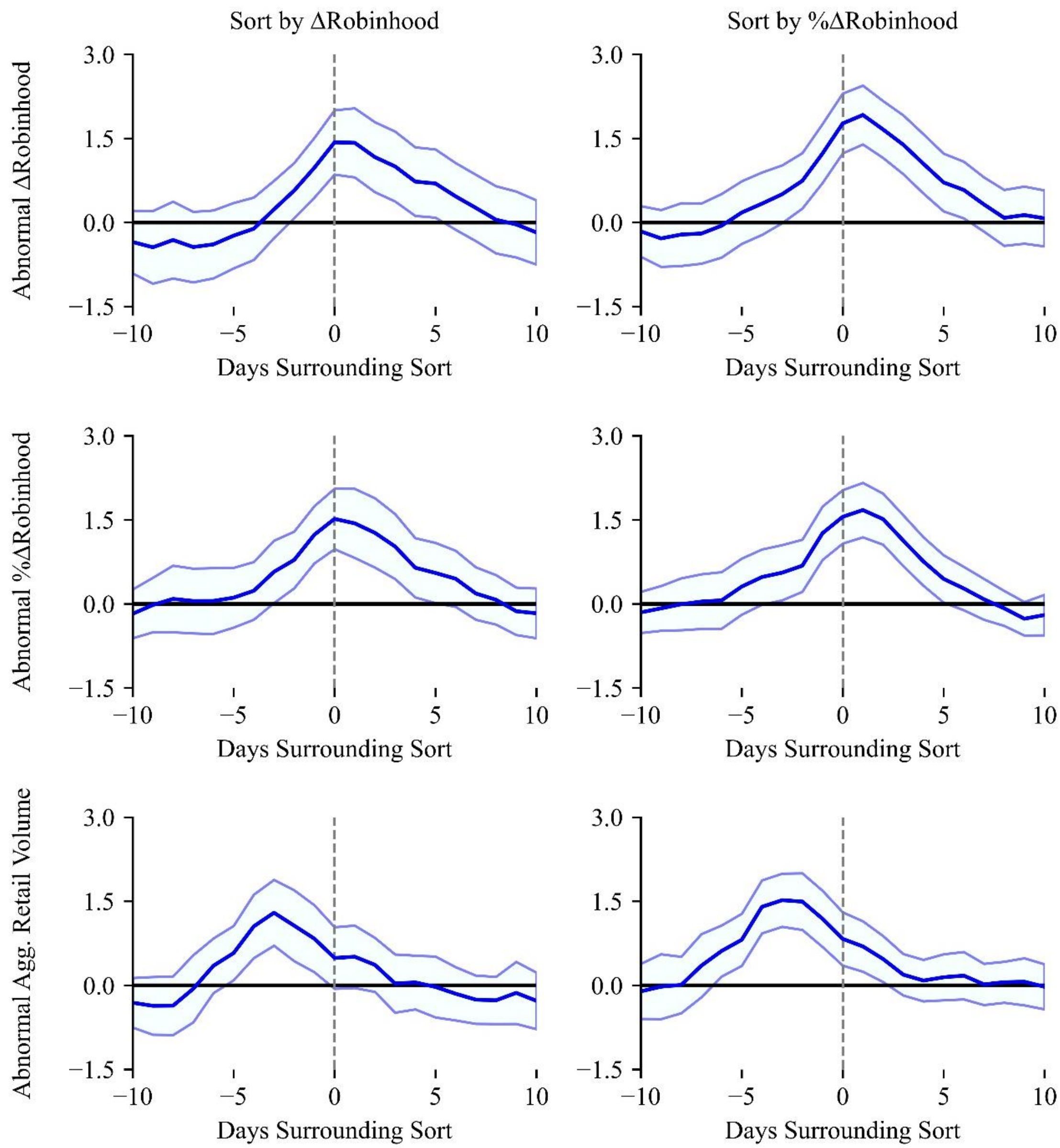

Figure IA2. Retail Activity Surrounding Periods of High Changes in Robinhood Ownership. High change in ownership (ΔRobinhood) or percentage change in ownership (%ΔRobinhood) days are defined on day 0 as being in the top quintile of stocks according to changes in ownership. Abnormal activity on days -10 to +10 are estimated relative to a 20-day moving average benchmark from day -30 to -11, standardized to the interval -1 to 1. Estimates of abnormal activity are indicated by the solid blue line and are obtained from ordinary least squares regressions to remove firm fixed effects, where the shaded area indicates the 99% confidence interval. *Abnormal ΔRobinhood* is the relative increase in aggregate changes in hourly Robinhood positions relative to the benchmark, *Abnormal %ΔRobinhood* is equivalent measure scaled by total Robinhood users, and *Abnormal Agg. Retail Volume* is the relative increase in aggregate retail volume using the using the classification described in Boehmer et al., 2020.

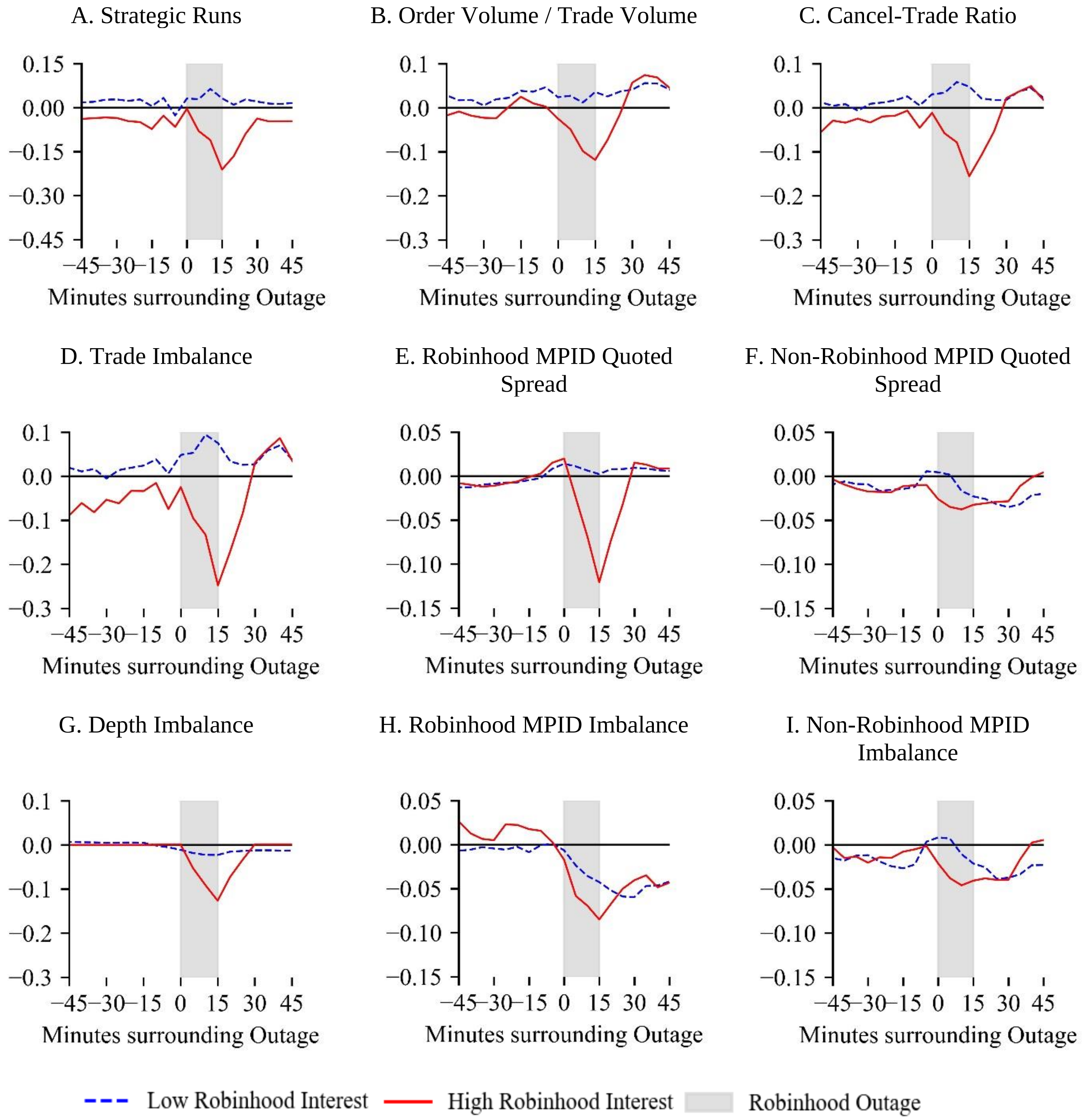

Figure IA3. HFT Activity Surrounding Robinhood Outages. This figure illustrates changes in market activity surrounding Robinhood platform outages. The multiple panels show market activity measures for the subsample of stocks with high interest among Robinhood investors, proxied by the number of unique WallStreetBets mentions during the control period of 5 trading days prior to the outage, alongside the market activity for the subsample of stocks with low interest among Robinhood investors. The change in market activity in each panel is measured as the average firm's difference between the measure on the day of the outage minus the time-of-day matched measure during the control period, scaled by standard deviation of the control period. The panels represent the variables analyzed in Tables 8, 9, and 10 of the text. The plots consider Robinhood platform outages reported on Downdetector that last for 15 minutes and begin after 10:00 AM.

Table IA1. Robinhood Affiliated Nasdaq Market Makers

Panel A lists the Nasdaq dealers with payment for order flow arrangements with Robinhood during the 2020 sample period, and Panel B lists the remaining set of (Nasdaq and FINRA member) market makers.

Panel A: Robinhood-Affiliated Market Participant IDs

MPID	Name	MPID	Name
CTDL	Citadel Derivatives Group Llc	NITE	VIRTU Americas LLC
CDRG	Citadel Securities LLC	VIRT	Virtu Americas LLC
ETMM	G1 Execution Services, LLC	WSEA	WOLVERINE SECURITIES, LLC
TSSM	TWO SIGMA SECURITIES, LLC		
OHOS	TWO SIGMA SECURITIES, LLC		
SOHO	Two Sigma Securities, LLC		

Panel B: Unaffiliated Market Participant IDs

MPID	Name	MPID	Name
ALNC	A.G.P. / ALLIANCE GLOBAL PARTNERS	MAXM	Maxim Group LLC
AGIS	Aegis Capital Corp.	MZHO	Mizuho Securities USA LLC
AEXG	ALTERNATIVE EXECUTION GROUP	MSCO	MORGAN STANLEY & CO. LLC
RILY	B. RILEY SECURITIES, INC.	STXG	Muriel Siebert & Co, Inc
LEHM	Barclays Capital Inc./Le	NATL	National Securities Corporation
BCMX	BERENBERG CAPITAL MARKETS LLC	NEED	Needham & Company, LLC
BMOC	BMO Capital Markets Corp.	ALNC	Network 1 Financial Securities Inc.
BOSC	Boenning & Scattergood, Inc.	NORT	Northland Securities, Inc.
MLCO	Bofa Securities, Inc.	OPCO	Oppenheimer & Co. Inc.
KING	C. L. King & Associates, Inc.	OTAA	OTA LLC
ADAM	CANACCORD GENUITY INC.	PAUL	Paulson Investment Company, Inc.
CSTI	CANACCORD GENUITY LLC.	PIPR	Piper Sandler & Co.
CANT	Cantor Fitzgerald & Co.	PUMA	Puma Capital, Llc
CFGN	CELADON FINANCIAL GROUP LLC	LAFC	R. F. Lafferty & Co., Inc.
SBSH	Citigroup Global Markets Inc.	RAJA	Raymond James & Associates, Inc.
DOTC	COLLIERS SECURITIES LLC	RBCM	RBC CAPITAL MARKETS, LLC
COWN	Cowen and Company, LLC	BARD	Robert W. Baird & Co. Incorporated
CHLM	Craig-Hallum Capital Group LLC	ROTH	Roth Capital Partners, LLC
DADA	D.A. Davidson & Co.	SGAS	SG Americas Securities, LLC
FLTG	FLOW TRADERS U.S. LLC	SPHN	Stephens Inc.
GSCO	GOLDMAN SACHS & CO. LLC	STFL	Stifel, Nicolaus & Company, Incorporated
GRFN	GRIFFIN FINANCIAL GROUP, LLC	INTL	StoneX Financial Inc.
GTSM	GTS SECURITIES LLC	RHCO	Suntrust Robinson Humphrey, Inc.
GUGS	Guggenheim Securities, LLC	SUFI	Susquehanna Financial Group, LLP
HOVD	HOVDE GROUP, LLC	LEER	SVB LEERINK LLC
IMCC	IMC FINANCIAL MARKETS	BNCH	The Benchmark Company, LLC
IMPC	Imperial Capital, LLC	VERT	The Vertical Trading Group, LLC
JPMS	J.P. Morgan Securities LLC	TRLN	Tradelink Securities, LLC
JSCA	JANE STREET CAPITAL, LLC	TLSA	TRADELINK SECURITIES, LLC
JANY	Janney Montgomery Scott Inc.	UBSS	UBS Securities LLC
JEFF	JEFFERIES LLC	WABR	Wall Street Access
JSSF	JMP Securities LLC	VNDM	Wall Street Access
JGUN	Joseph Gunnar & Co. LLC	WEDB	WEDBUSH SECURITIES INC.
KBWI	Keefe, Bruyette & Woods, Inc.	WCHV	WELLS FARGO SECURITIES, LLC
KEYB	KEYBANC CAPITAL MARKETS INC.	WBLR	WILLIAM BLAIR
LTCO	Ladenburg, Thalmann & Co., Inc.	WDCO	Wilson-Davis & Co., Inc.

Table IA2. Summary Statistics for Robinhood Holdings

The table presents descriptive statistics for stocks sorted into portfolios by Robinhood ownership. The sample includes 2,015 stocks held by Robinhood investors during the months of January to August 2020. We require stocks in the sample to have a daily minimum of 50 Robinhood users, a weekly average of 500 Robinhood users, and have data on the CRSP, COMPUSTAT, and TAQ databases. The table reports averages of firm characteristics partitioned according to weekly quintiles of Robinhood holdings. Variables are defined in Appendix A.

	Q1	Q2	Q3	Q4	Q5
Stocks in Quintile	391	390	390	390	389
Robinhood Owners Holding Stock	394	775	1,406	3,033	37,553
WallStreetBets Mentions from Previous Week	1.71	4.27	2.13	11.67	630.2
Trading Volume (Previous Week, Millions)	20.02	28.56	37.41	59	360.01
Trading Intensity (Previous Week)	1248.56	1598.34	2117.61	3035.4	8169.94
Agg. Retail Volume (Previous Week, Millions)	0.92	1.43	2.18	4.12	54.25
Firm Size (Assets in Millions)	6,320	6,918	9,704	17,903	62,119
Book-to-Market Ratio	0.79	0.69	0.54	0.66	0.55
Quoted Spread (Basis Points)	108.33	72.16	69.39	44.55	24.16
Effective Spread (Basis Points)	192.95	128.98	167.79	138.57	144.66
Realized Spread (Basis Points)	112.73	79.95	81.6	63.25	106.04
Price Impact (Basis Points)	81.28	55.67	84.6	71.8	75.99
5-minute Volatility (Basis Points)	189.04	151.06	170.84	258.65	211.43
Strategic Runs	1.46	1.56	1.69	1.98	2.76
Order Volume / Trade Volume	144.25	140.16	132.83	142.28	137.6
Cancel-Trade Ratio	12.43	12.77	12.99	14.74	16.92
Robinhood Market Maker Spreads (BPs)	112.03	72.82	58.35	108.06	150.57
Other Market Maker Spreads (BPs)	96.05	78.89	63.75	88.89	134.04
Trade Imbalance (BPs)	111.41	140.42	85.46	42.69	94.82
Depth-Weighted Imbalance (BPs)	90.35	119.76	93.45	111.22	169.57
Robinhood Market Maker Depth Imbalance (BPs)	57.38	113.56	118.34	150.3	204.76
Other Market Maker Depth Imbalance (BPs)	54.08	51.76	110.97	117.31	156.71

Table IA3. Retail Broker FAQ Webpage Categories among Website Visitors in 2020

The table presents website usage patterns of Robinhood and four other retail brokers using data obtained from SimilarWeb and AlexaInternet in July of 2020. The table illustrates the most visited FAQ topic pages among the broker websites, excluding account-related questions or FAQ topics not provided by all brokers, i.e. retirement account related questions. Question categories are aggregated across similar question types and ranked according to the prevalence of the FAQ topic on the website, where prevalence is measured as the number of FAQ web page visits divided by the total web page visits of the broker, expressed as page views per 1,000 site visitors.

	Robinhood		Other Retail Brokers	
Rank	FAQ Category	Visits /1,000	FAQ Category	Visits /1,000
1	What is the Stock Market	6.49	What are Stock Splits	1.67
2	What is the DJIA	6.07	What is an ETF	1.48
3	What is the S&P 500	5.78	What are Puts and Calls	1.45
4	What is a PE Ratio	5.73	What are the Different Order Types	1.41
5	What are Different Order Types	4.96	How to Trade IPOs	1.32
6	What is a Fiscal Year	4.72	What is RSI	1.25
7	What are Extended Hours	4.36	How to Find Investments	1.22
8	How to Trade / Invest	4.24	How are Investments Taxed	1.20
9	How to Find Investments	3.97	Mutual Funds vs ETFs	1.15
10	What is Pattern Day Trading	3.83	Trading Fees	1.14

Table IA4. Robustness: Percentage Changes in Robinhood Ownership as the Proxy for Expected Robinhood Trading

The Table repeats the analysis in Tables 4, 5, and 6 using percentage changes in Robinhood ownership (instead of level changes) as the proxy for expected Robinhood trading during outages. Panel A presents the trading variables from Table 4 along with the five-minute return volatility measure from Table 6. Panel B shows the results for the market quality measures analyzed in Table 5.

Panel A: Robinhood Platform Outages, Trading, and Volatility

	Robinhood Outages				Pseudo Outages			
	Trading Volume	Trading Intensity	BJZZ Volume	Return Volatility	Trading Volume	Trading Intensity	BJZZ Volume	Return Volatility
$RH_{i,d-1} \times Outage_t$	-0.114**	-0.101**	-0.053	-11.802*	-0.045	-0.038	-0.017	0.053
	(-2.06)	(-2.414)	(-0.936)	(-1.896)	(-1.148)	(-1.137)	(-0.412)	(0.040)
$RH_{i,d-1}$	0.387***	0.288***	0.534***	1.511	0.415***	0.334***	0.463***	2.002
	(12.573)	(13.059)	(14.981)	(0.282)	(15.391)	(11.541)	(13.851)	(1.287)
$Outage_t$	0.165	0.056	0.193	1.668	-0.029	-0.024	-0.009	2.728
	(1.3)	(0.389)	(1.43)	(0.303)	(-0.356)	(-0.294)	(-0.161)	(1.107)
Firm Clusters	2,015	2,015	2,015	2,015	2,001	2,001	2,001	2,001
Δ R-Squared (%)	1.8017	0.9678	1.1984	0.0013	2.5081	0.5096	1.0791	0.0012

Panel B: Robinhood Platform Outages and Stock Market Liquidity

	Robinhood Outages				Pseudo Outages			
	Quoted Spread	Effective Spread	Realized Spread	Price Impact	Quoted Spread	Effective Spread	Realized Spread	Price Impact
$RH_{i,d-1} \times Outage_t$	-3.167**	-5.825*	-5.816**	-4.151*	-0.316	-0.035	2.2	1.167
	(-2.535)	(-1.929)	(-2.4)	(-1.844)	(-0.442)	(-0.025)	(1.439)	(0.914)
$RH_{i,d-1}$	-2.683***	-1.804	-4.358**	2.355	-1.616***	-4.177*	-2.876*	-0.87
	(-5.097)	(-0.494)	(-2.27)	(0.984)	(-3.967)	(-1.732)	(-1.647)	(-0.62)
$Outage_t$	4.622	6.608	0.599	4.077	0.629	-0.46	-0.789	0.05
	(0.91)	(0.933)	(0.13)	(1.058)	(0.988)	(-0.402)	(-0.571)	(0.067)
Firm Clusters	2,015	2,015	2,015	2,015	2,001	2,001	2,001	2,001
Δ R-Squared (%)	0.2187	0.0029	0.0049	0.0016	0.1001	0.0032	0.0013	0.0002

Table IA5. Robustness. The table repeats Table 7 in the text without suppressing the regression output.

Panel A: Remove Firm-Outage Events with a 20% or Greater Spike in WallStreetBets Mentions on Outage Day

Dependent Variable	Trading Volume	Trading Intensity	Quoted Spread	Effective Spread	Realized Spread	Price Impact	5-Minute Volatility
Sorted by WSB							
$RH_{i,d-1} \times Outage_t$	-0.102***	-0.074**	-2.958**	-6.391*	-5.186*	-5.573**	-9.977**
	(-2.794)	(-2.326)	(-2.051)	(-1.843)	(-1.65)	(-2.065)	(-2.375)
$RH_{i,d-1}$	0.341***	0.224***	-2.006***	-9.747	-13.565**	-2.29	-8.688
	(7.959)	(6.712)	(-2.919)	(-1.357)	(-2.021)	(-0.607)	(-0.912)
$Outage_t$	0.16	0.047	4.595	6.61	0.517	4.276	8.385*
	(1.33)	(0.345)	(0.865)	(0.938)	(0.115)	(1.078)	(1.775)
Firm Clusters	2,015	2,015	2,015	2,015	2,015	2,015	2,015
Δ R-Squared (%)	0.6360	0.2571	0.1086	0.0082	0.0121	0.0026	0.0171
Sorted by RH User Change							
$RH_{i,d-1} \times Outage_t$	-0.133***	-0.095**	-2.83**	-6.591**	-9.312***	-8.784***	-11.72**
	(-2.622)	(-2.418)	(-2.36)	(-1.982)	(-3.507)	(-2.849)	(-2.361)
$RH_{i,d-1}$	0.547***	0.42***	-3.427***	2.991	0.340	4.732	8.272
	(13.962)	(15.418)	(-4.946)	(0.507)	(0.106)	(1.278)	(0.756)
$Outage_t$	0.166	0.051	4.600	6.701	1.337	4.916	8.887*
	(1.354)	(0.366)	(0.875)	(0.945)	(0.291)	(1.237)	(1.803)
Firm Clusters	2,015	2,015	2,015	2,015	2,015	2,015	2,015
Δ R-Squared (%)	2.1997	1.2882	0.1930	0.0023	0.0029	0.0047	0.0036

Panel B: Exclude Platform Outages that begin before 9:45 AM

Dependent Variable	Trading Volume	Trading Intensity	Quoted Spread	Effective Spread	Realized Spread	Price Impact	5-Minute Volatility
Sorted by WSB							
$RH_{i,d-1} \times Outage_t$	-0.087**	-0.067**	-2.86**	-5.936*	-5.103*	-4.876*	-16.566**
	(-2.294)	(-2.123)	(-2.02)	(-1.789)	(-1.842)	(-1.954)	(-2.025)
$RH_{i,d-1}$	0.333***	0.219***	-1.986***	-9.512	-12.689**	-2.198	28.829**
	(7.932)	(6.771)	(-2.912)	(-1.371)	(-2.032)	(-0.613)	(1.974)
$Outage_t$	0.154	0.044	3.81	6.004	0.025	3.658	-1.020
	(1.202)	(0.3)	(0.695)	(0.809)	(0.005)	(0.91)	(-0.835)
Firm Clusters	2,015	2,015	2,015	2,015	2,015	2,015	2,015
Δ R-Squared (%)	0.6287	0.2536	0.0918	0.0077	0.0112	0.0021	0.0185

Table IA5. Robustness (continued)

Panel B: Exclude Platform Outages that begin before 9:45 AM (continued)

Sorted by RH User Change							
$RH_{i,d-1} \times Outage_t$	-0.122**	-0.085**	-2.789**	-5.886*	-8.856***	-7.976***	-17.704**
	(-2.379)	(-2.273)	(-2.347)	(-1.8)	(-3.43)	(-2.665)	(-2.158)
$RH_{i,d-1}$	0.536***	0.409***	-3.392***	3.148	-0.361	4.706	9.548
	(13.609)	(15.032)	(-4.971)	(0.543)	(-0.115)	(1.295)	(0.784)
$Outage_t$	0.161	0.047	3.815	6.042	0.807	4.299	1.381
	(1.237)	(0.32)	(0.703)	(0.809)	(0.167)	(1.066)	(0.256)
Firm Clusters	2,015	2,015	2,015	2,015	2,015	2,015	2,015
Δ R-Squared (%)	2.1657	1.2548	0.1773	0.0020	0.0029	0.0042	0.0037

Panel C: Exclude All Platform Outages in March 2020

Dependent Variable	Trading Volume	Trading Intensity	Quoted Spread	Effective Spread	Realized Spread	Price Impact	5-Minute Volatility
Sorted by WSB							
$RH_{i,d-1} \times Outage_t$	-0.061*	-0.04	-5.873*	-5.567*	-2.906	-6.225**	-19.950**
	(-1.663)	(-0.717)	(-1.831)	(-1.744)	(-1.322)	(-2.241)	(-2.263)
$RH_{i,d-1}$	0.467***	0.296***	-1.295***	-0.826**	1.428	4.388	10.994
	(10.102)	(7.835)	'(-2.892)	'(-2.458)	(0.471)	(1.245)	(0.815)
$Outage_t$	0.128	0.085	-3.005	-1.254	0.652	-0.746	3.785
	(0.631)	(0.618)	'(-1.293)	(-1.037)	(0.164)	(-0.261)	(0.441)
Firm Clusters	2,002	2,002	2,002	2,002	2,002	2,002	2,002
Δ R-Squared (%)	1.0805	0.4505	0.0789	0.0010	0.0003	0.0024	0.0035
Sorted by RH User Change							
$RH_{i,d-1} \times Outage_t$	-0.105**	-0.142**	-1.035	-5.235**	-5.543**	-1.853	-2.247
	(-2.461)	(-1.996)	(-0.817)	(-2.321)	(-2.122)	(-0.826)	(-0.8)
$RH_{i,d-1}$	0.675***	0.633***	-4.819***	-2.271	-2.272	2.151	-5.083
	(15.521)	(15.444)	(-7.338)	(-0.757)	(-0.7)	(0.636)	(-0.569)
$Outage_t$	0.136	0.264***	0.059	1.265	1.192	-1.549	4.054
	(0.664)	(3.148)	(0.009)	(0.281)	(0.297)	(-0.575)	(0.483)
Firm Clusters	2,002	2,002	2,002	2,002	2,002	2,002	2,002
Δ R-Squared (%)	3.2920	1.8546	0.2257	0.0006	0.0018	0.0007	0.0019

Table IA5. Robustness (continued)

Panel D: Match Platform Outage Event Windows to Placebo Windows

Dependent Variable	Trading Volume	Trading Intensity	Quoted Spread	Effective Spread	Realized Spread	Price Impact	5-Minute Volatility
Sorted by WSB							
$RH_{i,d-1} \times Outage_t$	-0.077**	-0.038*	-3.107**	-9.843**	-4.252*	-4.995**	-3.788*
	(-2.025)	(-1.696)	(-2.311)	(-2.346)	(-1.674)	(-1.960)	(-1.647)
$RH_{i,d-1}$	0.257***	0.23***	-1.468**	-5.735	-3.090	-2.001	0.605
	(5.424)	(5.386)	(-2.294)	(-1.108)	(-1.359)	(-0.608)	(0.188)
$Outage_t$	0.152	0.043	3.236	4.157	0.608	2.337	2.293
	(1.220)	(0.160)	(0.696)	(0.657)	(0.135)	(0.699)	(0.705)
Firm Clusters	2,015	2,015	2,015	2,015	2,015	2,015	2,015
Δ R-Squared (%)	0.4627	0.0989	0.1129	0.0084	0.0018	0.0026	0.001
Sorted by RH User Change							
$RH_{i,d-1} \times Outage_t$	-0.056**	-0.077**	-3.736***	-5.191*	-3.075*	-5.811***	-9.132***
	(-2.059)	(-2.025)	(-3.152)	(-1.771)	(-1.851)	(-2.712)	(-3.427)
$RH_{i,d-1}$	0.531***	0.517***	-2.657***	0.3	-2.78	2.575	3.489
	(14.107)	(12.919)	(-4.226)	(0.07)	(-1.078)	(1.031)	(1.353)
$Outage_t$	0.165	0.056	3.382	3.339	0.413	2.544	3.372
	(1.324)	(0.205)	(0.734)	(0.519)	(0.091)	(0.755)	(1.051)
Firm Clusters	2,015	2,015	2,015	2,015	2,015	2,015	2,015
Δ R-Squared (%)	2.1524	0.6252	0.2271	0.0014	0.0015	0.0025	0.0056

Panel E: Measure Benchmark Control Period -6 to -10 Days before Platform Outage (Instead of -1 to -5)

Dependent Variable	Trading Volume	Trading Intensity	Quoted Spread	Effective Spread	Realized Spread	Price Impact	5-Minute Volatility
Sorted by WSB							
$RH_{i,d-1} \times Outage_t$	-0.116**	-0.159***	-2.684*	-12.101**	-8.357**	-6.96**	-15.502**
	(-2.199)	(-3.544)	(-1.867)	(-2.411)	(-2.401)	(-2.227)	(-2.162)
$RH_{i,d-1}$	0.241***	0.234***	-0.768	4.819	2.405	3.833	-0.68
	(5.18)	(5.511)	(-1.236)	(1.047)	(1.118)	(1.256)	(-0.075)
$Outage_t$	0.012	-0.062	5.008	4.503	2.387	3.564	-0.717
	(0.093)	(-0.433)	(1.216)	(1.082)	(1.18)	(1.227)	(-0.148)
Firm Clusters	2,015	2,015	2,015	2,015	2,015	2,015	2,015
Δ R-Squared (%)	0.2892	0.1052	0.1773	0.0068	0.0031	0.0039	0.0033
Sorted by RH User Change							
$RH_{i,d-1} \times Outage_t$	-0.122**	-0.136**	-3.287***	-8.666**	-8.431***	-7.146**	-13.822**
	(-1.985)	(-2.439)	(-2.894)	(-2.341)	(-2.739)	(-2.532)	(-2.35)
$RH_{i,d-1}$	0.387***	0.414***	-0.947*	6.008	0.603	5.352*	8.914
	(10.371)	(11.504)	(-1.811)	(1.157)	(0.21)	(1.726)	(0.888)
$Outage_t$	0.013	-0.065	5.162	3.956	2.487	3.66	-0.847
	(0.101)	(-0.462)	(1.27)	(1.024)	(1.287)	(1.34)	(-0.192)
Firm Clusters	2,015	2,015	2,015	2,015	2,015	2,015	2,015
Δ R-Squared (%)	1.0282	0.3953	0.2181	0.0052	0.0034	0.0056	0.0034

Table IA5. Robustness (continued)

Panel F: Require an Average of 1000 Robinhood Owners Prior to the Outage

Dependent Variable	Trading Volume	Trading Intensity	Quoted Spread	Effective Spread	Realized Spread	Price Impact	5-Minute Volatility
Sorted by WSB							
$RH_{i,d-1} \times Outage_t$	-0.044*	-0.022**	-3.361**	-14.026*	-5.864*	-2.224*	-2.838**
	(1.769)	(-2.179)	(-2.268)	(-1.759)	(-1.795)	(-1.775)	(-2.074)
$RH_{i,d-1}$	0.299***	0.245***	-1.39*	-30.594*	-27.972*	-12.457*	-84.942**
	(5.671)	(5.149)	(-1.706)	(-1.721)	(-1.829)	(-1.674)	(-2.133)
$Outage_t$	0.149	0.08	-4.639	-5.938	11.378	-10.08	29.425
	(1.085)	(0.283)	(0.899)	(0.817)	(1.091)	(-1.377)	(1.017)
Firm Clusters	1,561	1,561	1,561	1,561	1,561	1,561	1,561
Δ R-Squared (%)	0.6242	0.1257	0.0445	0.0109	0.0039	0.0011	0.0015
Sorted by RH User Change							
$RH_{i,d-1} \times Outage_t$	-0.061**	-0.019*	-4.163***	-11.765**	-7.158	-5.076*	-8.389
	(-2.231)	(-1.745)	(-3.427)	(-2.35)	(-1.02)	(-1.829)	(-1.598)
$RH_{i,d-1}$	0.555***	0.492***	-2.815***	-17.331*	-18.619**	-5.05	-29.492*
	(11.951)	(11.359)	(-3.73)	(-1.72)	(-1.972)	(-0.993)	(-1.811)
$Outage_t$	0.16	0.088	4.811	5.58	11.687	-9.496	26.441
	(1.151)	(0.309)	(0.947)	(0.741)	(1.137)	(-1.286)	(0.956)
Firm Clusters	1,561	1,561	1,561	1,561	1,561	1,561	1,561
Δ R-Squared (%)	2.4948	0.6290	0.0890	0.0051	0.0027	0.0006	0.0003