# Retail Trader Sophistication and Stock Market Quality: Evidence from Brokerage Outages

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**Abstract**

We study brokerage platform outages to examine how heterogeneity in retail investor sophistication influences their impact on financial markets. We contrast outages at Robinhood, which caters to inexperienced investors, with outages at more traditional retail brokers. Exogenous negative shocks to Robinhood (traditional broker) participation are associated with reduced (increased) market order imbalances, consistent with unsophisticated investors being more likely to herd. Robinhood (traditional broker) outages are associated with increased (decreased) market liquidity and lower (higher) return volatility. The findings are consistent with inexperienced retail investors creating inventory risks that harm liquidity, whereas other retail trading improves market quality.

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## 1. Introduction

Individual investor stock market participation has grown substantially in recent years. Retail volume now accounts for 20% of stock market activity, roughly double the rate from a decade ago (McCabe, 2021). Robinhood has contributed significantly to this development (Basak, 2020),[1] with innovative features such as zero commissions, user-friendly interfaces, and no account minimums, drawing many first-time investors to the stock market.[2] Given their lack of experience, these new retail investors are often characterized as having lower financial sophistication than retail investors at traditional brokerage firms. In this article, we study the financial market implications of heterogeneity in retail investor sophistication.

Aggregate measures of retail order flow have been shown to be contrarian in nature and predictive of future short-term stock returns, which has been attributed in part to market-enhancing liquidity provision (e.g. Kaniel, Saar, and Titman, 2008; Barrot, Kaniel, and Sraer, 2016; Boehmer and Song, 2020). On the other hand, inexperienced investors are prone to return chasing and attention-based trading (Goetzmann and Kumar, 2008; Greenwood and Nagel, 2009; Bianchi, 2018). In particular, Barber, Huang, Odean, and Schwarz (2021) show that Robinhood investors are more likely than other retail investors to herd into certain stocks. While retail noise traders could contribute to market liquidity by diluting the effects of informed traders (e.g. Glosten and Milgrom, 1985; Kyle, 1985), momentum-oriented herding by unsophisticated investors may create volatility and harm liquidity by creating inventory risks for market makers (e.g. Ho and Stoll, 1981; Grossman and Miller, 1988; Hendershott and Menkveld, 2014).

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[1] For example, 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.

[2] Robinhood's regulatory filings state that "millions of our customers are using Robinhood to enter the financial markets for the first time." 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).

Existing evidence on the effects of retail investors on financial markets is mixed. Foucault, Sraer, and Thesmar (2011) study a French legal reform that discouraged speculative and leveraged retail trading and find that stock market quality improved following the regulation change. In contrast, Peress and Schmidt (2020) find evidence that reduced retail trading is associated with lower stock market liquidity using distracting US news stories to reflect the absence of noise traders. We argue that retail investor heterogeneity may play an important role, and we examine brokerage platform outages to study the effects of retail investor clienteles on financial markets. Specifically, we contrast outages at Robinhood, which caters to inexperienced retail investors, with outages at more traditional retail brokerages (TD Ameritrade, Charles Schwab, and E-Trade).

We begin by documenting important differences in retail investor clienteles across brokers. We find no evidence that changes in Robinhood ownership are positively associated with future returns, contrasting with existing evidence for broader measures of retail order flow (Kaniel, Saar, and Titman, 2008; Kelley and Tetlock, 2013, Boehmer, Jones, Zhang, and Zhang, 2020 ). While Robinhood investors are more likely to purchase stocks that were recently discussed on Reddit WallStreetBets, aggregate retail order imbalances in these stocks are negative after controlling for firm characteristics. In general, Robinhood investors tend to be momentum-oriented, whereas aggregate retail order flow is contrarian. Controlling for lagged returns, we observe that aggregate retail order imbalances are negatively related to lagged changes in Robinhood breadth of ownership. Taken together, the trading evidence points towards lower expertise among Robinhood investors that is associated with liquidity-demanding behavior, whereas more sophisticated retail investors may provide liquidity to markets.

Although lengthy brokerage outages are rare, DownDetector.com, a web platform that compiles user complaints, lists 96 separate outages in which at least 200 users report outages during our January 2019 – June 2021 sample period (37 platform outages at Robinhood and 59 outages at traditional retail brokers). The median length of the outages in the sample is 30 minutes. Our approach for capturing the effects of retail investors on financial markets involves comparing market quality during platform outages to similar times of day over the previous week. We use indicator variables to contrast the effects of outages on stocks with high predicted retail trading relative to other stocks. The difference-in-differences type approach helps mitigate concerns that outages may be related to market-wide news, and we conduct several robustness tests, including pseudo outage analysis, to address concerns that outages may be endogenous.

We find that brokerage outages have a meaningful effect on trading activity. Stocks with high expected retail trading experience significantly lower trading intensity and volume during platform outages. For example, Robinhood outages are associated with 3.2% lower volume among stocks with high expected Robinhood trading, after controlling firm and day fixed effects. Analogously, outages at traditional brokers are associated 2.6% lower volume for stocks with high expected aggregate retail trading.

Our motivating premise is that the financial market implications of retail investors may vary with their level of sophistication. In particular, if unsophisticated retail investors are more likely to herd by trading on the same side of the market (e.g. Barber, et al., 2021), their presence may contribute to market imbalances. The outage evidence supports this view. Specifically, Robinhood outages are associated with reduced trade imbalances and depth-weighted quote imbalances in Robinhood-favored stocks. In contrast, market imbalances increase during outages at traditional brokers, suggesting that in aggregate retail investors have the effect of reducing market imbalances in retail-oriented stocks.

We hypothesize that momentum-oriented herding by unsophisticated investors may have important effects for financial markets. We consider 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. For example, we find that Robinhood outages are associated with quoted spreads that are 0.72 basis points lower, relative to a mean of 16.8 basis points. The implication is that imbalanced trading by Robinhood investors is harmful to market liquidity. In contrast, outages at other retail brokers are associated with reduced liquidity in stocks with high aggregate retail investor interest, with quoted spreads being 0.38 basis points higher during outages for stocks with high retail investor interest.

Robinhood outages are also associated with lower return volatility, whereas outages at other retail brokers coincide with increased 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. In particular, Robinhood outages are associated with 0.25 basis point lower transaction price volatility in Robinhood-favored stocks, meaningful relative to the mean of 12.5 basis points. Analogously, outages at traditional retail brokers are associated with 2.96% higher volatility for stocks with high expected aggregate retail trading. The outage evidence suggests that Robinhood traders contribute to volatility, in line with noise trading models such as DeLong, Shleifer, Summers, and Waldmann (1990), Campbell and Kyle (1993), and Llorente, Michaely, Saar, and Wang (2002), whereas other retail investors reduce volatility.

The evidence that outages are associated with changes in market quality raises the natural question of how off-exchange (dark) trading influences measures of public market (lit) quality. In recent times, high frequency trading (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 retail trading likely influences lit market quality through their internal algorithms.[3] FINRA regulation 5320 prohibits front-running of customer orders, and HFT firms implement information barriers between trading units so that the market making division does not obtain knowledge of customer orders from the wholesale division. However, the algorithms for both units will be influenced by the firm's overall position and internal risk tolerance.

Supporting inventory risk concerns, we find evidence consistent with greater liquidity provision during Robinhood outages specifically by HFTs with payment for order flow (PFOF) arrangements with Robinhood, and reduced liquidity provision by HFTs with PFOF arrangements with traditional retail brokers during their outages. For example, 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.

One important concern in our setting is that extreme market conditions may cause brokerage outages. We repeat the analysis for pseudo outages assumed to occur one hour after the actual event and find no evidence of shocks to trading or liquidity, which mitigates concerns that outages are driven by extreme market news. In addition, the results continue to hold if we exclude stocks with a high number of WallStreetBets mentions the day of the outage (that may have driven the outage) and also if we choose alternative pre-outage benchmark periods. Moreover, event-time figures provide convincing support for the interpretation that outages have a causal effect on trading and liquidity.

[3] For example, two of the three designated market maker firms on NYSE (Citadel Securities and Virtu Financial) also internalize orders for Robinhood.

Another potential concern is that broker institutional differences may play a role in our findings. All of the brokers we consider offered zero commissions during the sample period and have payment for order flow arrangements with wholesalers. Moreover, we note that the evidence that Robinhood outages are associated with more balanced trading and quoting activity, whereas the opposite holds for outages at traditional brokers, is more consistent with herding among less sophisticated investors leading to greater inventory costs rather than varying incentives to provide liquidity across brokers. Taken together, the findings support the view that unsophisticated retail traders can have negative effects on stock market quality, consistent with behavioral noise trader risk and dealer inventory models. In contrast, more experienced retail investors, who tend to be contrarian and are less likely to herd, have beneficial effects.

Our study helps reconcile the conflicting existing evidence regarding the effects of retail trading on market quality (Foucault et al., 2011; Peress and Schmidt, 2020; Greene and Smart, 1999). While previous work emphasizes retail investors on average, our findings suggest that the impact of retail investors on financial markets depends on their level of investor sophistication, and in particular on the extent to which investors herd and trade in a momentum or contrarian fashion. We show that even short-lived shocks to retail trading can significantly impact inventory risks in modern markets.[4]

In addition, our research adds to the literature that examines the effects of social interactions, including social media, on financial markets. Several studies find evidence that social media can provide investment value (Chen, De, Hu, and Hwang, 2014; Jame, Johnston, Markov, and Wolfe, 2016; Farrell, Green, Jame, and Markov, 2020), whereas other work suggests that

[4] Shkilko and Sokolov (2020) study the market quality effects of weather-induced shocks to microwave networks and find that liquidity providers react very quickly to changes in weather, consistent with liquidity providers reacting quickly to the information shocks associated with brokerage outages.

social media may spread stale news or intensify behavioral biases (Heimer, 2016; Cookson, Engelberg, and Mullins, 2020; Bali, Hirshleifer, Peng, and Yang, 2021; Pedersen, 2021). Bradley, Hanousek, Jame, and Xiao (2021) study a "Due Diligence" subset of Reddit WallStreetBets posts and find that these reports positively predict returns at the beginning of their sample period but reverse more recently. 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 trading by unsophisticated retail investors that have implications for market quality.

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, Kiefer, and O'Hara 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 retail traders can elevate or reduce inventory risk depending on the clientele. Robinhood retail investors tend to behave as momentum traders and are more likely to herd, and the outage evidence is consistent with Robinhood traders decreasing market quality by contributing to the inventory risk of wholesalers with PFOF arrangements with Robinhood. In contrast, aggregate retail investors tend to behave as contrarian investors and are less likely to herd. As a result, their presence leads to improved market quality and is consistent with these investors having a stabilizing effect on wholesaler inventory risk.[5]

[5] 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 Kyle, Samadi, and Tuzun, 2011; Shkilko and Sokolov, 2020). For example, van Kervel and Menkveld (2019) find evidence that HFTs increase execution costs for large institutional orders, whereas Korajczyk and Murphy (2019) argue that HFTs lower transaction costs for small, uninformed trades. Our evidence that Robinhood outages are associated with reduced market imbalances, while the opposite holds for traditional brokers, is more consistent with variation in inventory risks across clienteles rather than HFTs exploiting retail investors.

Our work is related to contemporaneous studies of Robinhood investors. Welch (2021) 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. (2021) finds that attention-induced herding by Robinhood investors is accompanied by large price movements and subsequent reversals. Van der Beck and Jaunin (2021) estimate a structural model to argue that Robinhood investors have an outsized effect on stock prices due to the inelastic nature of institutional demand. Hu, Jones, Zhang, and Zhang (2021) show Robinhood investors react to Reddit web postings, but do not explore measures of market quality. Glossner, Matos, Ramelli, and Wagner (2021) highlight that Robinhood investors tended to purchase stocks during the pandemic that institutions sold, consistent with liquidity provision.[6] Ozik, Sadka, and Shen (2021) 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 stocks with high expected trading, which may help explain the differential implications for market quality.

## 2. Data and Descriptive Statistics

This section describes the data and key variables used in the analysis, including retail ownership and trading variables, market quality variables, and measures of social media activity.

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

*2.1 Robinhood Breadth of Ownership Data*

Robinhood launched in 2015 with innovative features such as no commissions, no account minimums, and a user-friendly app that embedded aspects of gamification (Schifrin and Gara, 2021). In 2020, Robinhood had 13 million accounts, most of them first time investors, giving them about the same or more accounts than some of the other major retail brokers, such as Schwab (12.7 million accounts) or E-Trade (5.5 million). Although Robinhood account sizes are smaller than traditional retail brokerages,[7] Robinhood users traded nine times as many shares as E-Trade customers and 40 times as many shares as Charles Schwab customers per dollar in the average customer account in the first quarter of 2020 (Popper, 2020). Academic research also highlights Robinhood's significant impact. In particular, van der Beck and Jaunin (2021) build on the work of Gabaix and Koijen (2021) to argue that Robinhood investors have an outsized effect on stock prices due to the inelastic nature of institutional demand.

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.[8] 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

[7] Robinhood's mean account balance is between $1000 and $5000 (Venkateswaran, 2019), compared with $47,000 in the heavily studied US retail brokerage sample from the 1990s (e.g., Barber and Odean, 2001)
[8] Robinhood ended the practice of displaying number of users in August 2020 in part due to the actions of Robintrack, voicing concerns that the information might be used to disadvantage Robinhood investors (e.g., Ponczek, 2020).

Center for Research in Securities Prices (CRSP) data. We measure holdings changes for horizons longer than an hour by summing hourly holding changes.[9]

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. The resulting dataset is comprised of stock-day observations during the January 2019 – June 2021 sample period used to study broker outages.[10] We use these data to compute measures of Robinhood ownership 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 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.

[9] A stock-day observation with missing data is filled in with the value of the most recent valid observation within three trading days, otherwise it is left as missing.

[10] Although the Robintrack data are available July 2018 – August 2020, our sample period begins in 2019 as there are few outages 2018. We are able to extend the outage analysis beyond August of 2020 by using alternative proxies for Robinhood interest which we describe in Section 4.1.2.

*2.3 Measures of Market Quality and Market Maker Quotes*

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 defined as $2\times D_k(\ln(P_k) - \ln(M_{k+5min}))$, where $M_{k+5min}$ is the 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 is defined as the percentage change from the prevailing mid-quote at the time of the transaction to the mid-quote 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.

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 10% of the quoted midpoint, and winsorizing at the 99th percentile of orders according to order size.

Additionally, 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 a retail broker, which then allows us to measure the quoted spread and imbalance of each wholesaler that is directly impacted by retail broker outages. Table IA1 in the Internet Appendix lists the set of retail-affiliated MPIDs (i.e. Citadel, Virtu, G1X, and Two Sigma) and the remaining set of Nasdaq and FINRA member market makers.[11]

*2.4 Social Media*

The role that social media plays in retail investor interest is gauged using the number of times that a stock is mentioned on the Reddit message board WallStreetBets (r/wallstreetbets). We use an automated script to parse the WallStreetBets forum, and we obtain all the posts and comments during the sample period. 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, while avoiding overlap between stock tickers and acronyms (Appendix B provides details). Our measure of social media interest in a given stock is the daily sum of mentions by unique users on WallStreetBets.

*2.5 Sample Description and Summary Statistics*

We rely on data filters to construct the sample. Since the identification strategy focuses on stocks with the potential for high expected retail trading, we exclude stocks with few retail owners

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

or limited retail trading. Specifically, 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 platform outages, and a daily minimum of 5,000 shares traded in aggregate retail volume. Additionally, we require that sample stocks have prices above $1 so that microcaps do not distort interpretations of the results. Finally, we require that sample firms have data in the CRSP, COMPUSTAT, TAQ and ITCH databases. The sample includes 1,889 stocks that meet the data filters for the sample period of January 2019 to June 2021, which is the period during which we study brokerage outages.

Table 1 presents sample summary statistics. Observations are averaged across stocks each week and then across weeks. We observe that sample stocks are owned by 9,795 Robinhood investors on average, although the distribution is skewed, as the median number of Robinhood owners of a stock is 1,404. Robinhood Trading is also highly skewed. While the mean absolute daily change in users is 83, the standard deviation is 548.[12] Our clientele analysis in the next section emphasizes social media posting on WallStreetBets. Table 1 shows that the average stock has 73 unique mentions on WallStreetBets per week, although this is similarly skewed, with a standard deviation of 904 mentions.

## 3. Retail Investor Clienteles at Robinhood and Traditional Retail Brokers

Robinhood has sought to attract inexperienced investors, for example offering students cash prizes to open an account using their school email address (Rudegeair and McCabe, 2021), and it has fewer investor research and education offerings than other retail brokers.[13] In this

[12] Although the magnitudes of hourly changes in breadth of ownership are small for many stocks, ownership changes provide a proxy for trading by Robinhood investors with existing positions. Supporting this view, Barber et al. (2021) find that retail ownership changes and order flow are highly correlated (0.87) in the Barber and Odean (2000) retail investor sample.

[13] https://www.stockbrokers.com/guides/online-stock-brokers

section, we examine whether differences in retail investor clienteles result in differences in trading behavior.

We begin by offering descriptive evidence on the sophistication of Robinhood investors versus investors at traditional retail brokers 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 other major retail brokerages. The findings are tabulated in Table IA2 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 traditional retail 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 the relation between retail trading and future returns to explore whether retail clienteles can be 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 et al., 2008; Kaniel, et al., 2012; Kelley and Tetlock, 2013, 2017; Barrot et al., 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, and 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:

$$Ret_{i,[d,d+\tau]} = \alpha + \beta_1 RH_{i,d-1}^{Change} + \beta_2 AggRetailOIB_{i,d-1} + \gamma' \boldsymbol{Controls}_{i,d-1} + \varepsilon_{i,[d,d+\tau]}. \quad (1)$$

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. We also include the aggregate retail order flow variable ($AggRetailOIB_{i,d-1}$) 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 control variables that are known predictors of returns: past returns, as well as firm characteristics such as *Market Cap*, *Book-to-Market*, and *Skewness*.

Table 2 reports the results, with Panel A presenting the regression estimates for weekly changes in the number of Robinhood owners, and Panel B using percentage changes in the number of owners. 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. The estimated coefficients on Robinhood ownership are generally negative, and some of the coefficients are significantly different from zero, providing broader evidence of the herding reversal findings in Barber et al. (2021). 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. Although retail trades in general positively predict future returns, Robinhood investors on average appear to behave as noise traders.

*3.2 The Determinants of Retail Investor Trading*

The return evidence from previous section suggests that Robinhood investors trade differently from the aggregate retail traders. In this section, we investigate heterogeneity among retail investors by analyzing the determinants of trading activity for both Robinhood investors and aggregate retail investors. Barber et al. (2021) show that Robinhood investors tend to herd into certain stocks, and we conjecture that Robinhood investors are more significantly influenced by financial social media than other retail investors. Moreover, Goetzmann and Kumar (2008), Greenwood and Nagel (2009), and Bianchi (2018) find that less experienced investors are more prone to return chasing, and we anticipate that Robinhood investors may react differently to recent stock returns.

We estimate the following daily OLS regressions of retail trading direction on explanatory variables:

$$Y_{i,t} = \alpha + \sum_{q=2}^{5} \beta_q WSB_{i,t\text{-}1} + \delta' \boldsymbol{X_{i,t\text{-}1,rets.}} + \lambda' \boldsymbol{X_{i,t\text{-}1,firm}} + \gamma_1 Retail_{i,t\text{-}1} + \gamma_2 RH_{i,t\text{-}1} + \varepsilon_{i,t} \quad (2).$$

where the coefficients of $\beta_2$ to $\beta_5$ reflect the influence of social media on retail activity, in which we separate WSB mentions into quintiles to capture the non-linearity of stocks with high WSB interest. $\boldsymbol{X_{i,t\text{-}1,rets.}}$ is a vector of lagged return variables, $\boldsymbol{X_{i,t\text{-}1,firm}}$ is a vector of lagged firm-level control variables, and $Retail_{i,t\text{-}1}$ and $RH_{i,t\text{-}1}$ reflect lagged retail interest. The dependent variable is one of two measures of directional retail trading. In particular, we construct *Robinhood Purchases*, defined as the daily change in the number of Robinhood users that own the stock, and *Aggregate Retail Order Imbalance*, which is signed aggregate retail volume scaled by total retail volume (using the retail classification algorithm in Boehmer et al., 2020).

Table 3 presents the regression results. The coefficients on $WallStreetBets$ increase monotonically from quintiles 2 to quintiles 5 for the Robinhood Purchases specifications, suggesting the Robinhood trade activity is associated with high activity from the Reddit message board. Controlling for stock characteristics such as past returns, skewness, volume, size does not change the inference. On the other hand, the last column in Table 3 shows that the association between WallStreetBets and aggregate retail order imbalances is negative once we include other firm-related characteristics. The evidence suggests that Robinhood investors tend to trade in the same direction as the discussions on social media, whereas other retail investors are more likely to trade in contrarian ways after controlling for firm characteristics.

The loadings on the past stock return variables highlight another difference between Robinhood users and aggregate retail investors. For Robinhood purchases, the estimated coefficients on overnight return or returns from the previous day or week are significantly positive, suggesting that Robinhood investors tend to be momentum-oriented. However, under the aggregate retail specification, the negative estimated coefficients on past returns suggest aggregate order flow is contrarian, consistent with liquidity provision. Finally, controlling for lagged returns, we observe that aggregate retail order imbalances are negatively related to lagged changes in Robinhood breadth of ownership, highlighting the differences between Robinhood investors and aggregate retail investors.

## 4. The Differential Effects of Retail Investors on Financial Markets

This section examines how different types of individual investors impact market quality. The evidence in Section 3 is consistent with Robinhood investors behaving as uninformed, momentum traders. If such investors magnify fluctuations in market makers' inventory, market liquidity could deteriorate (Ho and Stoll, 1981; Grossman and Miller, 1988). Further, 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. In contrast, non-Robinhood retail investors exhibit contrarian trading, which could aid liquidity provision through reducing fluctuations in inventory.

### *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 et al., 2011; Peress and Schmidt, 2020). Our approach for isolating the effects of individual investors on financial markets relies on retail brokerage platform outages.[14] 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 retail investors are unable to participate due to technical difficulties with their brokerage platform.

#### *4.1.1 Brokerage Platform Outages*

Several retail brokers experienced outages during our sample period. Our emphasis is on the effects of different retail investor clienteles, and we separate Robinhood, which emphasizes inexperienced investors, from other traditional retail brokerages. In order to make the set of traditional brokers comparable to Robinhood, we require that they offer zero commission trades during the sample period. Further, we focus on brokers that have payment for order flow arrangements with wholesalers to help ensure that differences in institutional features do not influence the findings. The resulting set of traditional brokers includes Charles Schwab, E-Trade,

[14] Porter et al., (2008) examine a blackout-induced outage at the Copenhagen Stock Exchange to study the functioning of the cross-border NOREX alliance of exchanges.

and TD Ameritrade.[15] Among the other large zero-commission PFOF brokers, Interactive Brokers and Raymond James are not in the sample because they do not have sufficient outages reported on Downdetector. We also exclude Fidelity as it does not have payment for order flow arrangements with wholesalers, although in unreported analysis we find that the effects of Fidelity outages are very similar to the other traditional brokers.

We identify brokerage outages using Downdetector.com, a web platform that compiles user complaints. Outage information is updated at 15-minute time intervals and reflects both external user reports and internal verification checks.[16] 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 markets are open. We restrict the sample to outages unique to a single broker to alleviate concerns that outages may be driven by market-related factors.

The outage sample consists of 96 episodes that span approximately 6,585 total trading minutes; 2,465 for Robinhood and 4,120 for the other three traditional brokers combined. These numbers suggest that Robinhood (Traditional Brokers) experienced an outage in some form for approximately 1.01% (1.68%) of the open market time during our sample period. Figure 1, top panel, illustrates the days on which outages occur (in grey bars) for Robinhood alongside Robinhood ownership changes. The lower panel shows outages for traditional retail brokers and aggregate retail trading volume. Although the outages in March 2020 generally coincide with a period of high trading, outages appear fairly randomly distributed over time.

[15] All three of the traditional brokers we consider switched to zero commissions in October of 2019, and the majority of the outages in the Traditional Brokers sample occur after the switch to zero commissions (see Figure 1). Nonetheless, we verify in untabulated analysis that the results are similar if we exclude outages prior to the switch to zero commissions.

[16] "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/

### 4.1.2 Measuring Expected Retail Trading

Analyzing the effects of retail brokerage outages on financial markets requires a forecast of which stocks individual investors would have traded in the absence of the outage. To do so, we rely on stock-level projections of retail trading. We use a model similar to the one listed in Eq. (2), except that we define the y-variable differently, as this exercise is designed to analyze the determinants of retail trading volume, not trade direction (which was studied in Table 3). We analyze two alternative dependent variables, *Robinhood Trading*, defined as the daily sum of absolute hourly changes in Robinhood users that hold the stock, and *Aggregate Retail Volume / Volume*, which is the daily volume of aggregate retail trading (using Boehmer et al. 2020 to proxy for retail trading) scaled by total volume. We present the regression estimates in Table 4.

With these regression estimates in hand, we use the fitted values to predict retail trading during the outages. Specifically, the fitted regressions are estimated using expanding windows, where analysis of each outage uses the total sample of data up to the day prior to the outage. For the Robinhood (Traditional Broker) outages, we use projections from the regression in which *Robinhood Trading* (*Aggregate Retail Volume*) is the dependent variable. Since the Robintrack data end in August 2020, we use the fitted values of a modified model which omits *Robinhood* $Trading_{i,t-1}$ to predict Robinhood trading after August 2020.[17]

### 4.2 Broker Platform Outages and Trading Activity

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

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

[17] The prediction windows for aggregate retail trading expand throughout the sample, whereas the prediction windows for expected Robinhood trading expand until August 2020 and the coefficients are fixed afterwards.

The sample consists of 5-minute intervals, $t$, for each firm $i$ during the window on day $d$ when the broker 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 aggregate retail volume. The $RetTrd_{i,d-1}$ variable represent two alternative indicators. One is for stocks in the top quintile of expected Robinhood trading ($Robinhood_{i,d-1}$), and the other is the top quintile of expected aggregate retail volume ($Retail_{i,d-1}$), as described in Section 4.1.2. We also include firm, $\gamma_i$, and day, $\delta_d$, fixed effects in the model.

Table 5 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). Panel A presents results for high expected Robinhood trading, and Panel B for high expected aggregate retail trading. The first three columns present results during the Robinhood outages (Panel A) or traditional brokerage outages (Panel B). The key estimated coefficient is for the interaction between $RetTrd_{i,d-1}$ and $Outage_t$ which estimates how the trading measures are impacted by outages for stocks that either Robinhood investors (Panel A) or all individual investors (Panel B) are most interested in. We observe that trading activity drops significantly during both sets of outages for the high interest stocks. For example, Robinhood outages coincide with 3.2% lower volume for Robinhood stocks, and traditional retail brokerage outages generate 2.6% lower trading volume for the stocks retail investors in general are most interested in.

To address concerns that the outage effects may be spurious, we repeat the analysis for pseudo-events in the last three columns of Table 5. 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 $RetTrd_{i,d-1}$ and $Outage_t$ are close to zero and statistically insignificant, regardless of specification, suggesting that the drop in trading activity we observe for the high interest stocks is unique to the outages.

*4.3 Brokerage Platform Outages and Market Liquidity*

Having established that Robinhood materially impacts trading activity, we next consider whether Robinhood trading is significantly related to market quality. We begin this section by examining the effects of the outages on trade and depth imbalances. If Robinhood 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). On the other hand, if a retail investor clientele enhances liquidity, we would expect that their trading is negatively related to trade and depth imbalances.

Table 6 presents OLS regression estimates of the following model:

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

The dependent variable, $Imb_{i,t}$, represents alternative measures of inventory imbalances. We consider trade imbalances as well as depth-weighted imbalances, which captures asymmetry in total depth around the midpoint of the best bid and ask (these variables are defined in more detail in Appendix A). The independent variables are the same as those described for Eq. (3). Panel A presents results for the Robinhood outages and Panel B for the traditional brokerage outages. We observe that Robinhood outages are associated with reduced trade order imbalances and lower market depth-weighted imbalances for the stocks Robinhood investors favor, which is consistent with inventory risk unwinding when Robinhood traders cannot trade. In contrast, the imbalance measures increase during traditional brokerage outages for the stocks retail investors favor, suggesting that inventory risk increases during outages at traditional brokers. For robustness, we find that the key results become insignificant for the pseudo outage period (last 2 columns of Table 6).

We next consider the effects of the outages on various measures of stock liquidity by estimating the following model with OLS regressions:

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

Specifically, we analyze the effects of brokerage platform outages on *Quoted Spread*, *Effective Spread*, *Realized Spread*, and *Price Impact* for the stocks with the greatest expected Robinhood or general retail trading.

The first four columns in Table 7 present the estimated slope coefficients and *t*-statistics for the Robinhood outages (Panel A) and traditional retail brokerage outages (Panel B). We find that spreads are significantly lower during the outages for the high Robinhood stocks. For example, effective spreads are 0.98 basis points lower on average compared to a mean of 13.58 basis points, which translates to a drop in effective spreads of about 7.22%. Since these variables measure illiquidity, the results suggest that liquidity improves when Robinhood investors are unable to trade.

O'Hara (2015) highlights that market imbalances caused by classically uninformed traders can have effects similar to informed traders over the short time intervals of interest to market makers. In our setting, herding by Robinhood investors can create price pressure that extends beyond the five-minute horizon of the traditional price impact measure (Barber, et al., 2021). The evidence in Table 7 is consistent with this view, with Robinhood outages leading to significant reductions in measured price impact.

In contrast to the evidence on Robinhood investors, outages at traditional retail brokers are associated with reduced market quality. In particular, the spread measures significantly increase for stocks with high expected aggregate retail trading during outages, suggesting that liquidity deteriorates on average when non-Robinhood retail investors are unable to trade. We confirm in the last four columns of Table 7 that the significant liquidity effects disappear if we instead use pseudo-outages that are one hour after the actual outages end.[18]

*4.4 Brokerage Platform Outages and Price Volatility*

We next examine whether retail trading influences stock return volatility by analyzing brokerage platform outages with the following model, estimated with OLS regressions:

$$Vola_{i,t} = \alpha + \beta_1 RetTrd_{i,d-1} + \beta_2 Outage_t + \beta_3 RetTrd_{i,d-1} \times Outage_t + \gamma_i + \delta_d + \varepsilon_{i,t,} \quad (6)$$

where $Vola_{i,t}$ is measured from individual transaction prices for firm *i* during each five minute window *t*. The independent variables are the same as those in Eqs. (3)-(5). We present the estimates of this model in Table 8. We find that Robinhood platform outages are associated with significantly lower volatility for high Robinhood stocks, suggesting that an exogenous reduction in Robinhood traders leads to less volatility. As with the prior evidence, the outages at other retail brokers give the opposite result, as volatility significantly improves for the high-retail-interest stocks when these retail investors cannot trade. The analogous evidence for pseudo outages is economically negligible and statistically insignificant, confirming that the volatility results hold only during actual platform outages.

[18] Each regression in Table 7 includes firm fixed effects that capture the average level of the dependent variable over the full sample period, including potentially both low and high retail interest periods. The significant coefficients on *Robinhood* and *Retail* indicate that the characteristics that lead a stock to have high expected retail trading, such as recent returns and volume, coincide with periods of relatively high liquidity for the stock. The lack of significant effects during the pseudo outages, along with the strong parallel trend evidence illustrated in Figures 2 and 3, help alleviate concerns that stock characteristics may be driving the results.

*4.5 Robustness*

In this section, we perform a number of robustness checks for the results presented in Tables 5-8. An important potential concern in our setting is that 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 significant effects for pseudo-events measured one hour after actual events helps mitigates this concern. We perform additional robustness analyses, which we report in Table 9. For brevity we report only the interaction terms that capture the effects of outages on stocks with high expected Robinhood or general retail trading.

One concern is 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 can 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 9, 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 9). Additionally, well-publicized outages occurred on several days in March 2020, when markets experienced high volatility due to the developing Covid-19 pandemic. Although many of these days are already excluded from the analysis due to the sample restriction that omits simultaneous broker outages, we repeat the analysis after excluding all of the outages

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

that occurred in March of 2020 (6 of the 96 outage events, Panel C of Table 9). The key results remain robust, which does not support the view that outage effects are spuriously driven by market news.

Our benchmark period is measured using the week prior to the outage. In Panel D of Table 9, we repeat the analysis using a pre-outage benchmark window from day -10 through day -6, instead of day -5 through -1. The findings survive this robustness test. In Panel E, we raise the minimum threshold of retail investor interest by removing firms in the lowest quintile of predicted Robinhood trading (for Robinhood outages) and predicted aggregate retail trading (for traditional broker outages). Again, the findings remain robust.

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. In Panel F of Table 9, 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 outage to match the length of the pseudo window. The outage results remain robust.

Additionally, although we consider treated stocks as those with high predicted Robinhood trading for Robinhood outages and those with high aggregate retail trading for Traditional Broker outages, Panel G presents across-group evidence which continues to support the view that Robinhood investors harm liquidity while other retail investors improve it. For example, outages at Traditional Brokers lead to significantly lower liquidity in Robinhood-favored stocks, suggesting that the contrasting findings are not driven by underlying firm characteristics.

We report an additional robustness analysis in Table IA3 in the Internet Appendix, which presents the traditional broker evidence separately for each broker. The effects of outages on financial markets are consistent across Schwab, E-Trade, and Ameritrade, and 28 of the 30 coefficients are statistically significant.

Our final 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 and low retail interest. 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. So that the plots show pre-outage trends and have a consistent outage window, this sample is comprised of the 12 Robinhood and 14 traditional retail broker outages that occur after 10:00am and that last no longer than 15 minutes.

We plot the abnormal market quality measures in Figure 2 (Robinhood outage) and Figure 3 (traditional retail broker outages). The figures plot the 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 (illiquidity and volatility rise) for stocks with high expected Robinhood (aggregate retail) trading precisely during the outage window reported on Downdetector, while remaining relatively flat for the control set of firms. Moreover, the plots generally follow parallel trends prior to the outage, and market conditions begin to return to normal fairly quickly after the outage ends. Overall, the robustness checks provide convincing support for the interpretation that retail broker platform outages have causal effects on financial markets.

## 5. Retail Investors and Market Making Firms

The market quality evidence in the previous section 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 retail 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,[21] which suggests that information about retail trading may influence lit market quality directly through these firms' algorithms.

FINRA regulation 5320 prohibits front-running of customer orders, and 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.[22] As a result, shocks to the operations of the wholesale unit may influence liquidity provision by the market making unit. We explore this channel by studying individual market maker quoting behavior.

[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 and other retail brokers, are two of the three designated market maker firms on NYSE.

[22] Virtu Financial, Inc. states in their 2014 prospectus that "if our risk management system detects a trading strategy generating revenues outside of our preset limits it will freeze, or lockdown, that strategy and alert risk management personnel and management." https://www.sec.gov/Archives/edgar/data/1592386/000104746914002070/a2218589zs-1.htm

If the changes to market quality during outages are mediated by HFTs with payment for order flow arrangements with Robinhood or the other retail brokers, we would expect to observe changes specifically to the affiliated HFTs' quoting behavior. Although HFT market makers often quote anonymously, their algorithms govern their mandated publicly displayed quotes, and it is likely that material shocks to firm-wide retail order flow would influence the market maker quotes, which we identify with ITCH data (see Section 2.3). We explore this hypothesis in Table 10, which reports the results of estimating Equations (4) and (5) for depth imbalances and bid-ask spreads, respectively, measured from the quotes with the identities of Robinhood- or Traditional-Broker-affiliated dealers and unaffiliated dealers (listed in Table IA1 in the Internet Appendix). We report results for Robinhood outages in Panel A and Traditional Broker outages in Panel B.

The regression results show that for high expected Robinhood (aggregate retail) trading stocks, outages are associated with narrowing (widening) of market maker spreads and decreased (increased) depth imbalances for Robinhood (Traditional Broker) affiliated market makers. Further, the effects on spreads and depth imbalances are insignificant for the unaffiliated market maker quotes. These results are consistent with the notion that the effects of retail trading on market quality are facilitated through dealers with payment for order flow arrangements with retail brokers.

## 6. Conclusion

The rise of Robinhood, with its zero-commission trades and easy-to-use interface, has helped enable a dramatic increase in investor participation by a new class of retail traders. We examine how this new group of investors trades and impacts market quality relative to other retail investors from more traditional brokers. We find evidence that Robinhood trading is strongly positively related to lagged social media mentions, whereas WallStreetBets does not positively impact retail trading at more traditional brokers. Further, Robinhood investors tend to exhibit momentum trading, in contrast with other retail investors who tend to be contrarian, consistent with liquidity provision.

We exploit brokerage platform outages to measure the effects of the different retail investor clienteles on market quality. Our analysis indicates that during platform outages, 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. In contrast, outages at other retail brokers have the opposite effect. Measures of market quality significantly deteriorate in stocks with high expected aggregate retail volume during outages at traditional brokers, suggesting that retail traders from the more traditional brokers have a positive effect on 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.

Our final analysis examines the role HFTs play in mediating the effects of retail trading on financial markets. We observe that quoted bid-ask spreads narrow for Robinhood-affiliated HFTs and increase for Traditional-Broker-affiliated HFTs during outages. Further, decreases in trade and quote imbalance during Robinhood outages suggest that Robinhood investors enhance inventory risks for affiliated dealers, whereas increases in imbalances during outages at Traditional Brokers suggest that retail trading at the more traditional brokers leads to diminished inventory risks. The public quoting results highlight the interaction between off-exchange trading and public market quality.

## Appendix A: Variable Definitions

*A.1 Key Explanatory Variables*

- *Robinhood Change* – Stock *i'*s change in Robinhood ownership measured over hourly, daily, and weekly horizons. Winsorized at 1% tails. Source: Web Scraping.
- *Robinhood % Change* – Stock *i'*s change in Robinhood ownership measured over hourly, daily, and weekly horizons. Winsorized at 1% tails. Source: Web Scraping.
- $Robinhood_{i,d\text{-}1}$ – Indicator variable equal to one for stocks in top quintile of expected Robinhood Trading from fitted values (see Section 4.1.2).
- $Retail_{i,d\text{-}1}$ – Indicator variable equal to one for stocks in top quintile of expected aggregate retail trading from fitted values (see Section 4.1.2).
- *Outage* – An indicator variable that denotes periods experiencing brokerage platform outages (1 if an outage occurs during period *t* and 0 otherwise). Source: Downdetector

*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
- *Robinhood Purchases* (Table 3) – Stock *i'*s daily change in Robinhood users that hold the stock, Winsorized at 1% tails. Source: Web Scraping.
- *Robinhood Trading* (Table 4) – Stock *i'*s daily sum of absolute hourly changes in Robinhood users that hold the stock. Winsorized at 1% tails. Source: Web Scraping.
- *Aggregate Retail Order Imbalance* (Table 3) – Signed aggregate retail volume scaled by total retail volume, using Boehmer et al., (2020) to identify retail trades. Winsorized at 1% tails. Source: TAQ.
- *Aggregate Retail Volume / Volume* (Table 4) – Aggregate Retail Volume scaled by total Trading Volume.
- *Trading Volume* (Tables 5, 9) – Natural log of the total share volume. Winsorized at 1% tails. Source: TAQ.
- *Trading Intensity* (Tables 5, 9) – Natural log of the total number of trades. Winsorized at 1% tails. Source: TAQ.
- *Trade Imbalance* (Tables 6, 9) – 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 1% tails. Source: TAQ.
- *Depth-Weighted Imbalance* (Tables 6, 9) – 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. We exclude stub quotes and quotes more than 10% away from the NBBO. Source: Nasdaq TotalView ITCH.
- *Quoted Spread* (Tables 7, 9) – Equal-weighted average of best bid-ask spread, scaled by the midquote, during the intraday window. Winsorized at 1% tails. Source: TAQ.

- *Effective Spread* (Tables 7, 9) – Equal-weighted average of the effective spread during the intraday window. For each transaction, the effective spread is defined as $2\times|\ln(P_k) - \ln(M_k)|$, where $P$ is the trade price and $M$ is the prevailing midquote. Winsorized at 1% tails. Source: TAQ.
- *Realized Spread* (Tables 7, 9) – 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 *k*th transaction. Trade sign is based on Lee and Ready (1991) algorithm. Winsorized at 1% tails. Source: TAQ.
- *Price Impact* (Tables 7, 9) – 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 *k*th transaction. Winsorized at 1% tails. Source: TAQ.
- *Volatility* (Tables 8, 9) – The trade-based standard deviation of returns during the 5-minute period, if have a minimum of 10 trades. Winsorized at 1% tails. Source: TAQ.
- *Affiliated Market Maker Spreads* (Table 10) – The average distance between the best bid and best offer of market makers that have payment for order flow arrangements with the broker experiencing the outage. MPID is identified from Nasdaq TotalView ITCH (See Table IA1 for the list of affiliated Market Makers). Spreads are time-weighted for each MPID during each five-minute window, and then averaged across MPIDs. We exclude stub quotes and quotes more than 10% away from the NBBO.
- *Other Market Maker Spreads* (Table 10) – The average distance between the best bid and best offer of market makers that do not have payment for order flow arrangements with the broker experiencing the outage. MPID is identified from Nasdaq TotalView ITCH (See Table IA1 for complete list of unaffiliated market makers). Spreads are time-weighted for each MPID during each five-minute window, and then averaged across MPIDs. We exclude stub quotes and quotes more than 10% away from the NBBO.
- *Affiliated Market Maker Depth Imbalance* (Tables 10) – The depth-weighted imbalance for the orders with MPID attributions, where only orders from market makers that have payment for order flow arrangement with the broker experiencing the outage are included. MPID is identified from Nasdaq TotalView ITCH (See Table IA1 for a complete list of affiliated Market Makers). We exclude stub quotes and quotes more than 10% away from the NBBO.
- *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 the broker experiencing the outage are included. MPID is identified from Nasdaq TotalView ITCH (See Table IA1 for complete list of unaffiliated market makers). We exclude stub quotes and quotes more than 10% away from the NBBO.

### *A.3 Control Variables for Tables 2-4*

- *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. $Return_{Overnight}$

represents stock returns measured from the closing price on day *t*-1 to the opening price on day *t*. Winsorized at 1% tails. Source: CRSP.

- *Market Cap* – Each security's price multiplied by the number of shares outstanding. We log transform market equity and lag it by one day. Winsorized at 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 1% tails. Source: Compustat and CRSP
- *Return 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 1% tails. Source: CRSP.
- *$WallStreetBets_i$* – an indicator variable representing stocks in quintile *i* based on number of unique users who post about a stock on WallStreetBets over the previous five days. Source: Web Scraping.
- *Return Range* – is the high closing price minus the low closing price from the previous 60 day period. Source: CRSP.
- *Volume* – Natural log of the total share volume. Winsorized at 1% tails. Source: TAQ.
- *Price* – The price of the stock on day *t*-1.

## Appendix B: WallStreetBets Search Approach

We rely on natural language processing tools to identify stock mentions on the Reddit forum WallStreetBets. For each stock in our sample, we use company information to create a set of searchable tokens. Namely, the searchable tokens include ticker prepended by $, ticker without $ prepended, full company name including entity type (Inc., Co., LLC), full company name excluding entity type, first word of company name, and bi-grams of first two words in company name. To avoid misclassifications, we require the search tokens not to be contained in the 5000 most common words in the Oxford English Corpus (OEC), or the 5000 most common words or bigrams in the Top 10 Reddit forums in December 2018. We also remove common finance and social media acronyms. Non-unique searchable terms are removed so that each search token has a one-to-one mapping between the search term and stock. The algorithm is applied to the text from all posts and comments from WallStreetBets during the period of January 2019 to June 2021. The method is conservative in that it may not capture all mentions of an individual stock. However, it minimizes the likelihood of misidentifying stock mentions. Below are five examples:

| | Company Name (Ticker) | | | | |
|---|---|---|---|---|---|
| | American Airlines Group Inc. (AAL) | Apple, Inc. (AAPL) | Ford Motor Company (F) | Macy's Inc (M) | United States Steel Corporation (X) |
| Included Search Terms | | | | | |
| | $AAL, AAL, American Airlines Group Inc., American Airlines Group, American Airlines | $AAPL, AAPL, Apple Inc. | $F, Ford Motor Company, Ford Motor, Ford | Macy's Inc., Macy's | $X, United States Steel Corporation, United States Steel |
| Excluded Search Terms | | | | | |
| | American | Apple | F | $M, M | X, United States |

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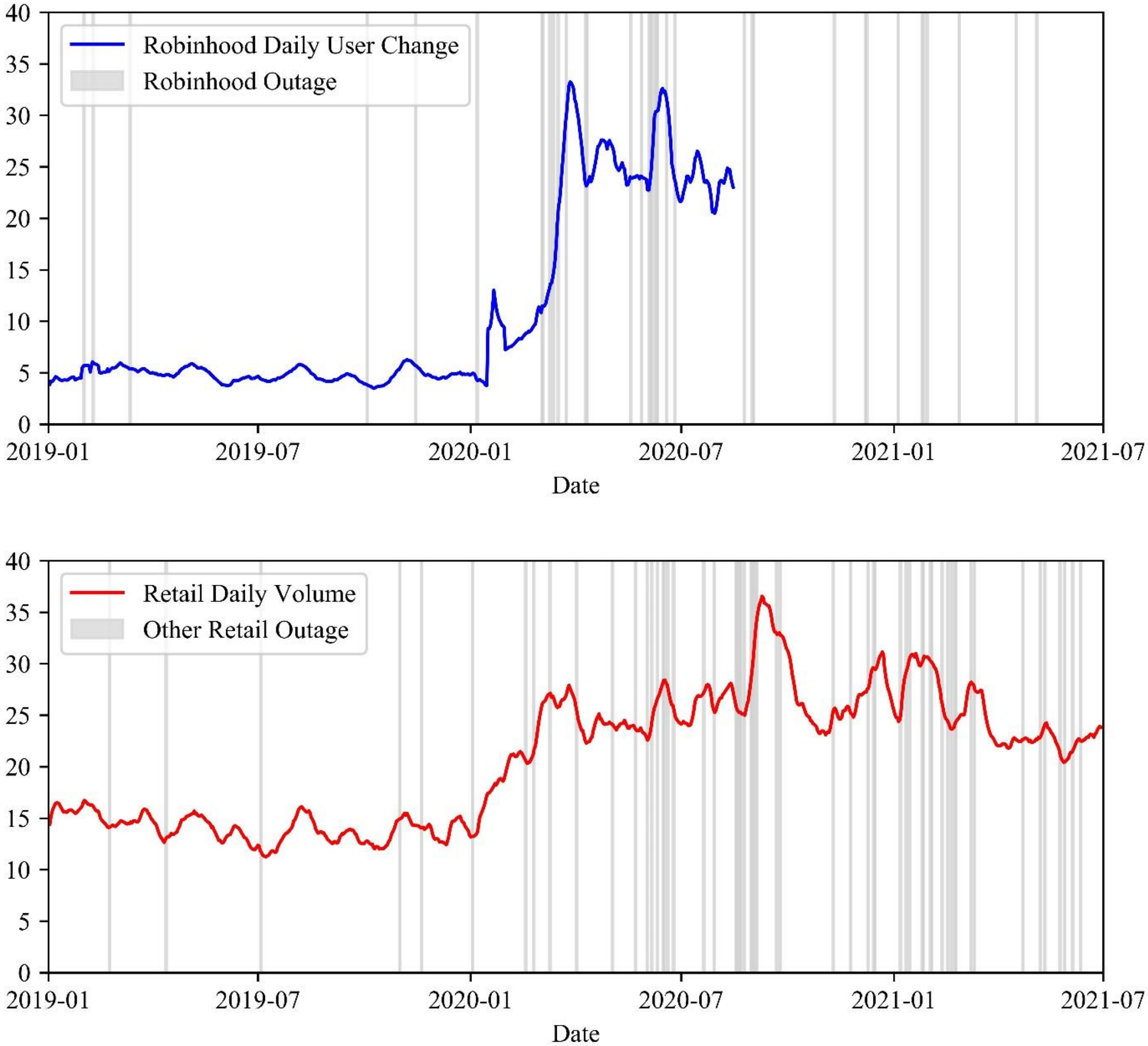


**Figure 1. Retail Trading and Broker Platform Outage Dates.** Panel A plots the cumulative absolute value of hourly changes of Robinhood user positions for the Jan. 2019 to Aug. 2020 and the days in which the Robinhood platform experienced an interruption during the regular trading hours of 9:30 to 16:00 EST through June 2021. Panel B plots aggregate retail trading volume and broker platform outage dates for the traditional retail brokers (E-Trade, Ameritrade, and Schwab). Platform outages are defined as having at least 200 outage reports on Downdetector.com.

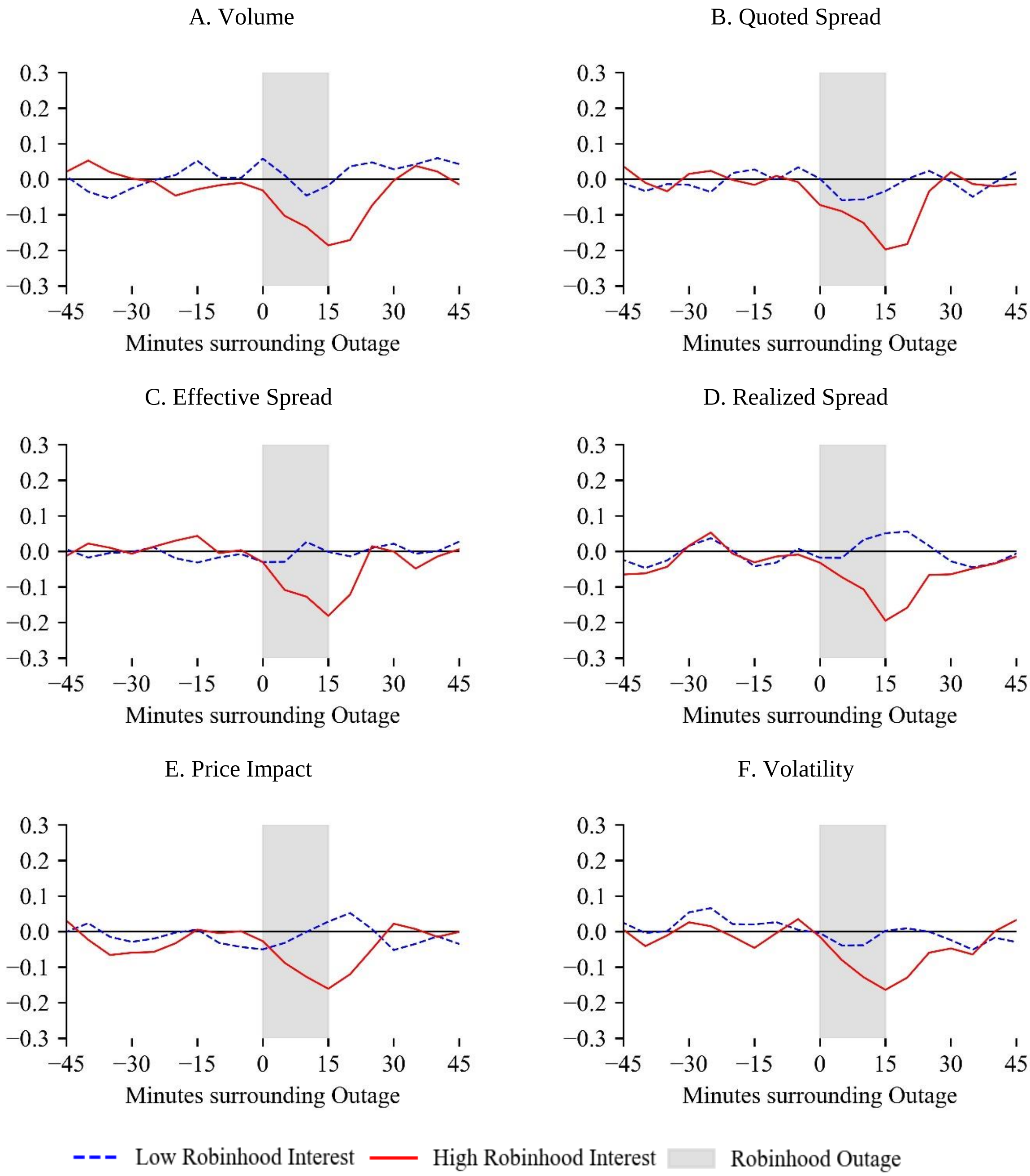


**Figure 2. Market Quality Surrounding Robinhood Outages.** The figure illustrates changes in market quality surrounding Robinhood platform outages. The multiple panels show alternative measures of market quality for the subsample of stocks with high interest among Robinhood investors, proxied by fitted value estimates of Robinhood user changes 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.

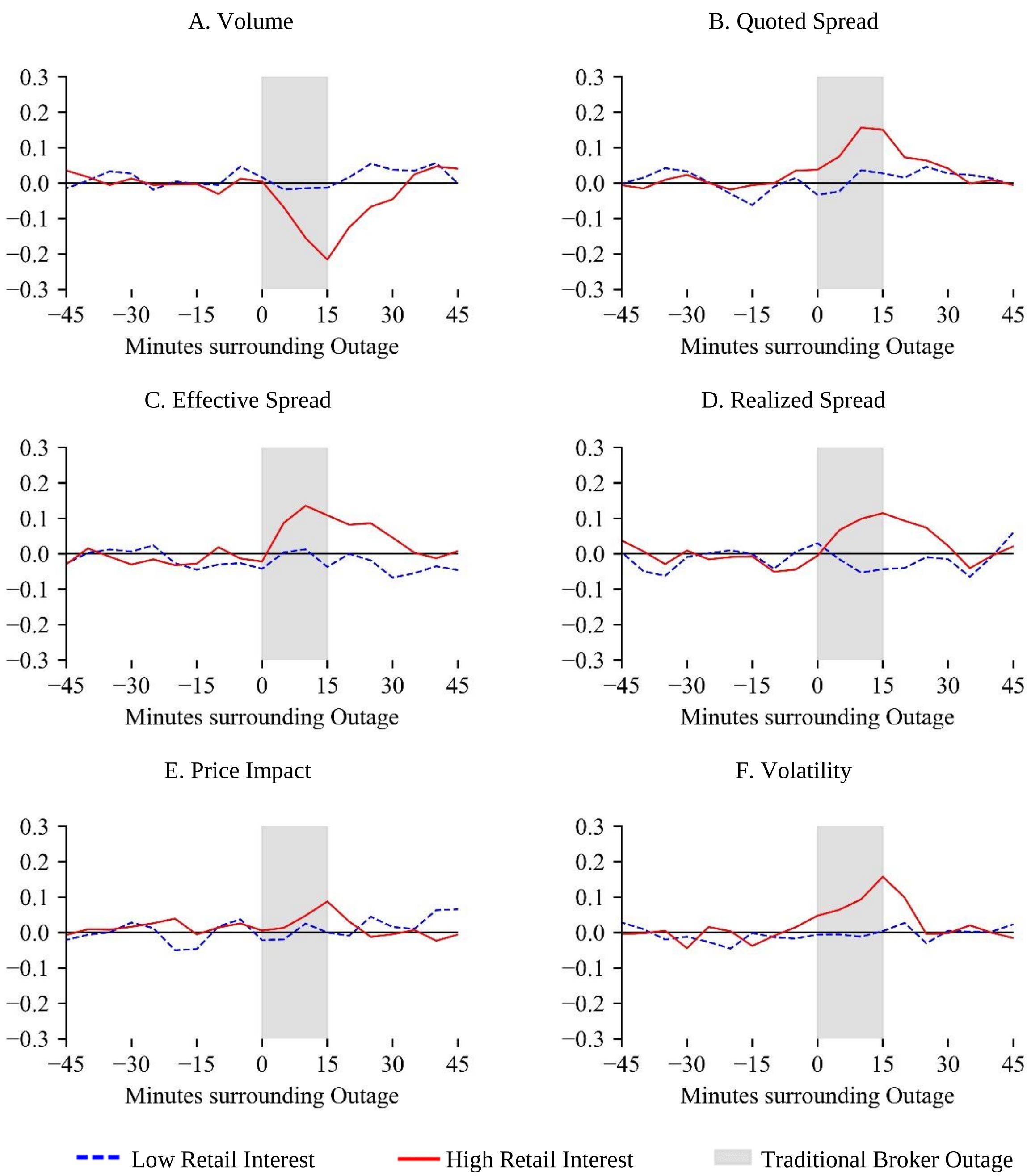


**Figure 3. Market Quality Surrounding Traditional Broker Outages.** The figure illustrates changes in market quality surrounding other retail broker platform outages. The multiple panels show alternative measures of market quality for the subsample of stocks with high interest among retail investors in aggregate, proxied by fitted value estimates of aggregate retail order imbalance 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 broker platform outages reported on Downdetector that last for 15 minutes and begin after 10:00 AM.

**Table 1. Summary Statistics for Retail Investors**

The table presents descriptive statistics for stocks commonly traded by retail investors. The sample includes 1,889 stocks that meet the data filters, and the sample period is January 2019 to June 2021. We require stocks in the sample to have a daily minimum of 50 Robinhood users, a daily minimum of 5,000 shares traded in aggregate retail volume, a weekly average of 500 Robinhood users in the week prior to platform outages, a stock price above $1, and to have data in the CRSP, COMPUSTAT, TAQ and ITCH 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, *Robinhood Trading* is the daily sum of absolute hourly changes in Robinhood users that hold the stock, *Robinhood Purchases* is the daily change in Robinhood users that hold the stock, *Agg. Retail Volume / Volume* is the daily volume of aggregate retail trades using the retail classification described in Boehmer et al., 2020 scaled by total volume, and *Agg. Retail Order Imbalance* is signed aggregate retail volume scaled by total retail volume. *Daily Returns* is the is the percentage change in daily stock prices, *Return Skewness* is the 60-day skewness of stock returns, and *Return Range* is the 60-day high closing price minus the 60-day low closing price. *Market Cap* and *Book-to-Market* are from the previous fiscal quarter-end, *Trading Volume* is the daily average of trading volume, *Trading Intensity* is the daily number of trades, and *Agg. Retail Volume* is the average of daily retail volume. 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. *Affiliated Market Maker Spreads* are the average MPID quoted spreads according to whether the firm has a payment for order flow arrangement with the retail broker. 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. *Affiliated Market Maker Depth Imbalance* (*Other Market Maker Depth Imbalance*) represent imbalances in the limit order book for market makers affiliated (not) with the retail broker.

| | Mean | Std Dev | 25$^{th}$ | Median | 75$^{th}$ |
|---|---|---|---|---|---|
| Robinhood Users Holding Stock | 9,795 | 42,025 | 607 | 1,404 | 4,147 |
| WallStreetBets Mentions from Previous Week | 73.2 | 903.6 | 4.6 | 8 | 19.4 |
| Robinhood Trading | 83.23 | 547.57 | 10.00 | 25.00 | 55.00 |
| Robinhood Purchases | 40.36 | 529.39 | -8.00 | 3.00 | 19.00 |
| Agg. Retail Volume / Volume | 0.06 | 0.07 | 0.02 | 0.04 | 0.08 |
| Agg. Retail Order Imbalance | 0.12 | 0.31 | -0.03 | 0.14 | 0.30 |
| Daily Returns (BPs) | 23.17 | 218.00 | -17.72 | 0.67 | 22.93 |
| Return Skewness (BPs) | 23.89 | 148.50 | -37.60 | 12.08 | 73.27 |
| Return Range (BPs) | 45.22 | 44.33 | 20.69 | 33.13 | 53.43 |
| Market Cap (Millions) | 18,698 | 38,795 | 1,339 | 4,148 | 16,060 |
| Book-to-Market Ratio | 0.38 | 0.47 | 0.08 | 0.21 | 0.61 |
| Trading Volume (Millions) | 10.32 | 24.93 | 1.29 | 3.16 | 8.51 |
| Trading Intensity (Previous Week) | 254.5 | 361.2 | 69.8 | 138.9 | 277.9 |
| Agg. Retail Volume (Previous Week, Millions) | 2.94 | 7.75 | 0.31 | 0.72 | 1.96 |
| Quoted Spread (BPs) | 16.77 | 15.46 | 6.02 | 11.89 | 22.02 |
| Effective Spread (BPs) | 13.58 | 11.52 | 5.46 | 10.08 | 17.80 |
| Realized Spread (BPs) | 4.69 | 9.08 | 0.17 | 1.34 | 6.24 |
| Price Impact (BPs) | 9.00 | 6.85 | 4.32 | 7.25 | 11.78 |
| 5-Minute Volatility (BPs) | 12.45 | 8.79 | 6.31 | 9.97 | 15.80 |
| Affiliated Market Maker Spread (BPs) | 38.07 | 7.29 | 21.88 | 27.44 | 47.72 |
| Other Market Maker Spread (BPs) | 36.99 | 19.92 | 17.24 | 21.11 | 38.83 |
| Trade Imbalance (BPs) | 44.62 | 18.24 | 31.02 | 46.29 | 58.55 |
| Depth-Weighted Imbalance (BPs) | 336.14 | 283.86 | 32.37 | 105.38 | 248.17 |
| Affiliated Market Maker Depth Imbalance (BPs) | 56.96 | 102.23 | 35.85 | 45.04 | 85.15 |
| Other Market Maker Depth Imbalance (BPs) | 6.27 | 76.21 | 32.24 | 5.73 | 88.39 |

**Table 2. Retail Trading and Stock Returns**

The table presents results from daily Fama-MacBeth regressions of stock returns on Robinhood ownership changes and aggregate retail trade imbalances. 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+τ] (in percent), is compounded over days *d* through *d+τ*, 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 are defined 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, 5,000 shares in average retail volume, and with a stock price of at least $1 during the months of January 2019 to August 2020, when the Robinhood ownership data end.

Panel A: Weekly Change in Robinhood Ownership

| | Return [1,3] | | Return [1,5] | | Return [1,20] | |
|---|---|---|---|---|---|---|
| Robinhood Change | -0.049 | -0.024 | -0.058 | -0.007 | -0.039 | 0.125 |
| | (-1.36) | (-0.69) | (-1.22) | (-0.16) | (-0.32) | (0.97) |
| Aggregate Retail OIB | | 0.239*** | | 0.217*** | | 0.546** |
| | | (4.81) | | (3.37) | | (2.14) |
| Ret[0] | | -0.030*** | | -0.038** | | -0.035 |
| | | (-2.86) | | (-2.48) | | (-1.28) |
| Ret[-1] | | 0.001 | | -0.015 | | -0.002 |
| | | (0.15) | | (-1.28) | | (-0.11) |
| Ret[-5,-1] | | -0.017** | | -0.016 | | -0.024 |
| | | (-2.21) | | (-1.48) | | (-1.07) |
| Market Cap[-1] | | -0.02 | | -0.03 | | -0.125 |
| | | (-0.72) | | (-0.65) | | (-0.60) |
| Book-to-Market | | -0.118** | | -0.170** | | -0.595 |
| | | (-2.38) | | (-2.01) | | (-1.62) |
| Skewness | | 0.026 | | 0.060** | | 0.11 |
| | | (1.36) | | (2.09) | | (1.14) |
| Observations | 664,481 | 561,403 | 664,286 | 561,239 | 662,805 | 560,055 |
| Average $R^2$ | 0.003 | 0.05 | 0.002 | 0.054 | 0.002 | 0.053 |

Panel B: Weekly Percentage Change in Robinhood Users

| | Return [1,3] | | Return [1,5] | | Return [1,20] | |
|---|---|---|---|---|---|---|
| Robinhood % Change | -0.161*** | -0.146*** | -0.217*** | -0.184*** | -0.218* | -0.189 |
| | (-3.41) | (-3.31) | (-3.88) | (-3.10) | (-1.91) | (-1.54) |
| Aggregate Retail OIB | | 0.253*** | | 0.237*** | | 0.565** |
| | | (4.96) | | (3.58) | | (2.24) |
| Ret[0] | | -0.026** | | -0.033** | | -0.03 |
| | | (-2.46) | | (-2.14) | | (-1.10) |
| Ret[-1] | | 0.003 | | -0.013 | | 0 |
| | | (0.30) | | (-1.09) | | (0.02) |
| Ret[-5,-1] | | -0.014* | | -0.013 | | -0.02 |
| | | (-1.87) | | (-1.16) | | (-0.90) |
| Market Cap[-1] | | -0.023 | | -0.033 | | -0.119 |
| | | (-0.82) | | (-0.73) | | (-0.58) |
| Book-to-Market | | -0.118** | | -0.170** | | -0.592 |
| | | (-2.40) | | (-2.04) | | (-1.62) |
| Skewness | | 0.027 | | 0.060** | | 0.115 |
| | | (1.37) | | (2.07) | | (1.20) |
| Observations | 664,475 | 561,402 | 664,280 | 561,238 | 662,799 | 560,054 |
| Average $R^2$ | 0.005 | 0.052 | 0.004 | 0.055 | 0.003 | 0.054 |

**Table 3. Retail Trader Sophistication and Determinants of Retail Trade Direction**

The table reports the effects of stock characteristics on retail position changes. The dependent variable in the first two columns is the daily change in Robinhood user positions, while the dependent variable in the latter two columns is the aggregate retail order imbalance. The determinants of retail position changes are estimated for each stock and day in the sample using OLS regressions. 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. See Table 1 and Appendix A for further details on variable definitions. We include common stocks with a daily minimum of 50 and weekly average of 500 Robinhood users, 5,000 shares in average retail volume, and with a stock price of at least $1.

| | Robinhood Purchases | | Agg. Retail Order Imbalance | |
|---|---|---|---|---|
| $WallStreetBets_2$ | 6.397*** | 1.795 | 0.006*** | -0.487 |
| | (5.431) | (0.57) | (2.805) | (-0.086) |
| $WallStreetBets_3$ | 11.882*** | -4.092 | 0.012*** | -0.482 |
| | (6.181) | (-0.693) | (3.801) | (-1.064) |
| $WallStreetBets_4$ | 10.759*** | 2.996** | 0.021*** | -0.747* |
| | (4.984) | (2.165) | (5.803) | (-1.855) |
| $WallStreetBets_5$ | 24.243*** | 7.579*** | 0.037*** | -0.928*** |
| | (4.067) | (3.947) | (7.494) | (-2.963) |
| $Return_{Overnight}$ | | 7.108*** | | -0.306*** |
| | | (9.484) | | (-8.806) |
| $Return_{[t-2 \text{ to } t-1]}$ | | 0.883** | | -0.159** |
| | | (2.337) | | (-2.181) |
| $Return_{[t-5 \text{ to } t-2]}$ | | 4.839** | | 0.019 |
| | | (2.191) | | (1.174) |
| Return Skewness | | 0.52*** | | 0.214*** |
| | | (3.921) | | (2.022) |
| Return Range | | 2.281* | | 0.394*** |
| | | (1.769) | | (3.537) |
| $Volume_{t-1}$ | | -0.461 | | 0.021*** |
| | | (-0.87) | | (2.786) |
| $Price_{t-1}$ | | 0.038* | | -0.0 |
| | | (1.816) | | (-0.171) |
| Market $Cap_{t-1}$ | | 0.088 | | -0.004* |
| | | (1.596) | | (-1.883) |
| Robinhood $Purch_{t-1}$ | | 0.946*** | | -0.004*** |
| | | (28.026) | | (-6.955) |
| Agg. Retail $OIB_{t-1}$ | | 8.406*** | | 0.826*** |
| | | (2.578) | | (72.933) |
| R-squared | 0.0122 | 0.6237 | 0.0309 | 0.3136 |

**Table 4. Measuring Expected Trading for Retail Investor Clienteles**

The table reports the effects of stock characteristics on retail investor trading activity. The dependent variable in the first three columns is the daily sum of hourly position changes of Robinhood investors, while the dependent variable in the latter three columns is the daily volume of aggregate retail trading scaled by total volume. The determinants of retail trading activity are estimated for each stock and day in the sample using OLS regressions. 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. See Table 1 and Appendix A for further details on variable definitions.

| | Robinhood Trading | | Agg. Retail Volume / Volume | |
|---|---|---|---|---|
| $WallStreetBets_2$ | 8.65 | -0.374 | 0.005 | -0.001 |
| | (0.135) | (-0.909) | (1.514) | (-0.966) |
| $WallStreetBets_3$ | 13.694*** | 0.983 | 0.009 | 0.001 |
| | (6.382) | (1.159) | (0.961) | (0.794) |
| $WallStreetBets_4$ | 9.062*** | 3.474** | 0.017*** | 0.001 |
| | (2.727) | (1.978) | (11.753) | (0.212) |
| $WallStreetBets_5$ | 41.516*** | 13.556*** | 0.024*** | 0.003 |
| | (5.913) | (3.285) | (10.569) | (1.397) |
| $Return_{Overnight}$ | 10.612*** | 3.572*** | 0.002*** | 0.001*** |
| | (11.234) | (8.117) | (14.627) | (5.593) |
| $Return_{[t-2 \text{ to } t-1]}$ | 7.713** | 11.108*** | 0.001*** | 0.013*** |
| | (2.495) | (8.447) | (10.508) | (12.501) |
| $Return_{[t-5 \text{ to } t-2]}$ | 6.993*** | 5.423 | 0.003* | -0.001 |
| | (4.624) | (0.985) | (1.863) | (-1.333) |
| Return Skewness | 0.803** | 0.55*** | 0.013*** | 0.003*** |
| | (2.281) | (3.43) | (6.814) | (5.266) |
| Return Range | 33.282*** | 0.877*** | 0.001** | 0.001** |
| | (5.466) | (2.988) | (2.306) | (2.301) |
| $Volume_{t-1}$ | 18.611*** | 0.73*** | 0.012*** | 0.000* |
| | (10.075) | (4.027) | (11.727) | (1.893) |
| $Price_{t-1}$ | 0.62* | 0.005** | 0.001*** | 0.000*** |
| | (1.897) | (2.234) | (6.757) | (3.758) |
| Market $Cap_{t-1}$ | 0.115 | 0.013 | 0.00 | 0.00 |
| | (0.091) | (1.177) | (1.343) | (0.864) |
| Robinhood $Trade_{t-1}$ | | 0.905*** | | -0.002 |
| | | (40.111) | | (-1.32) |
| Retail $Volume_{t-1}$ | | 3.232 | | 1.009*** |
| | | (0.347) | | (106.61) |
| R-squared | 0.215 | 0.805 | 0.238 | 0.860 |

**Table 5: Retail Broker Platform Outages and Trading Activity**

The table reports the effects of retail broker outages on trading activity for stocks with high retail interest. The sample consists of 5-minute intervals, *t*, for each firm *i* during the window on day *d* when the 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 columns report estimates for actual 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 retail broker outages are indicated by the indictor variable $Outage_t$. The variable $Robinhood_{i,d-1}$ is equal to one for stocks in the top quintile of predicted Robinhood trading activity and zero otherwise, and the variable $Retail_{i,d-1}$ is equal to one for stocks in the top quintile of predicted aggregate retail trading activity. We measure market activity during Robinhood platform outages in Panel A, and market activity during other retail broker platform outages in Panel B. 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. Each model specification includes firm and day fixed effects, and Δ R-squared values are incremental after fixed effects. See Appendix A for further details on variable definitions.

Panel A: Stocks with High Expected Robinhood Trading during Robinhood Platform Outages

| | Robinhood Outages | | | Pseudo Outages | | |
|---|---|---|---|---|---|---|
| | Trading Volume | Trading Intensity | Retail Volume | Trading Volume | Trading Intensity | Retail Volume |
| $Robinhood_{i,d-1} \times Outage_t$ | -0.032** | -0.018** | -0.052*** | 0.008 | 0.006 | -0.021 |
| | (-2.066) | (-2.316) | (-2.359) | (0.378) | (0.295) | (-0.149) |
| $Robinhood_{i,d-1}$ | 0.434*** | 0.35*** | 0.469*** | 0.352*** | 0.275*** | 0.609*** |
| | (4.749) | (4.453) | (3.298) | (3.266) | (2.979) | (2.618) |
| $Outage_t$ | -0.071 | -0.056 | -0.153 | -0.032 | -0.027 | -0.068 |
| | (-0.863) | (-0.956) | (-0.800) | (-0.602) | (-0.666) | (-0.313) |
| Observations | 1,826,443 | 1,826,443 | 1,826,443 | 1,731,100 | 1,731,100 | 1,731,100 |
| Firm Clusters | 1964 | 1964 | 1964 | 1964 | 1964 | 1964 |
| Δ R-squared (%) | 1.872 | 2.189 | 1.49 | 1.461 | 1.622 | 1.351 |

Panel B: Stocks with High Expected Aggregate Retail Trading during Outages at Traditional Brokers

| | Traditional Broker Outages | | | Pseudo Outages | | |
|---|---|---|---|---|---|---|
| | Trading Volume | Trading Intensity | Retail Volume | Trading Volume | Trading Intensity | Retail Volume |
| $Retail_{i,d-1} \times Outage_t$ | -0.026** | -0.021** | -0.107*** | -0.010 | -0.007 | -0.068 |
| | (-2.192) | (-1.985) | (-3.091) | (-0.455) | (-0.39) | (-0.213) |
| $Retail_{i,d-1}$ | 0.183*** | 0.135*** | 0.311** | 0.168*** | 0.12*** | 0.349*** |
| | (2.840) | (3.099) | (2.276) | (3.614) | (3.762) | (2.945) |
| $Outage_t$ | 0.011 | 0.012 | 0.129 | -0.012 | -0.012 | 0.037 |
| | (0.127) | (0.217) | (1.185 ) | (-0.286) | (-0.309) | (0.276) |
| Observations | 3,452,964 | 3,452,964 | 3,452,964 | 3,215,633 | 3,215,633 | 3,215,633 |
| Firm Clusters | 1964 | 1964 | 1964 | 1964 | 1964 | 1964 |
| Δ R-squared (%) | 0.081 | 0.083 | 0.624 | 0.086 | 0.082 | 0.635 |

**Table 6. Retail Broker Platform Outages and Trade and Depth Order Imbalances**

The table reports the effects of retail broker outages on inventory imbalances for stocks with high retail interest. The dependent variable in each specification is a measure of either 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 sample consists of 5-minute intervals, *t*, for each firm *i* during the window on day *d* when the brokerage 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 Outage sample is the actual time window in which the retail 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 5, and Panel A represents the effect of Robinhood platform outages on stocks with predicted high Robinhood interest, and B reports results for the effect of traditional retail broker platform outages on stocks with high predicted aggregate retail interest. 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: Robinhood Platform Outages and Stocks with High Expected Robinhood Trading

| | Robinhood Outages | | Pseudo Outages | |
|---|---|---|---|---|
| | Trade Imbalances | Depth-Weighted Imbalances | Trade Imbalances | Depth-Weighted Imbalances |
| $Robinhood_{i,d-1} \times Outage_t$ | -17.538** | -27.738*** | 16.948 | -0.206 |
| | (-2.476) | (-3.335) | (0.253) | (-0.035) |
| $Robinhood_{i,d-1}$ | 45.049*** | 16.288** | 24.919*** | 9.646** |
| | (3.309) | (3.445) | (6.001) | (2.409) |
| $Outage_t$ | -22.206 | -6.146 | -65.529 | -8.818 |
| | (-0.157) | (-1.026) | (-1.192) | (-1.313) |
| Observations | 1,826,443 | 1,826,443 | 1,731,100 | 1,731,100 |
| Firm Clusters | 1964 | 1964 | 1964 | 1964 |
| Δ R-squared (%) | 6.714 | 3.825 | 3.543 | 1.127 |

Panel B: Traditional Brokerage Platform Outages and Stocks with High Expected Aggregate Retail Trading

| | Traditional Broker Outages | | Pseudo Outages | |
|---|---|---|---|---|
| | Trade Imbalances | Depth-Weighted Imbalances | Trade Imbalances | Depth-Weighted Imbalances |
| $Retail_{i,d-1} \times Outage_t$ | 8.521** | 16.294*** | -10.311 | -0.822 |
| | (2.3) | (3.325) | (-1.437) | (-0.18) |
| $Retail_{i,d-1}$ | -32.974 | -0.373 | 12.699 | -3.34 |
| | (-1.421) | (-0.087) | (1.354) | (-0.671) |
| $Outage_t$ | 25.21 | 0.369 | 32.927 | -3.516 |
| | (1.158) | (0.083) | (0.507) | (-0.91) |
| Observations | 3,452,964 | 3,452,964 | 3,215,633 | 3,215,633 |
| Firm Clusters | 1964 | 1964 | 1964 | 1964 |
| Δ R-squared (%) | 4.533 | 3.078 | 2.596 | 0.326 |

**Table 7. Retail Broker Platform Outages and Stock Liquidity**

The table reports the effects of Robinhood outages on measures of liquidity for stocks with high retail interest. The sample consists of 5-minute intervals, *t*, for each firm *i* during the window on day *d* when the retail brokerage 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 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 5 and Section 4. Panel A represents the effect of Robinhood platform outages on stocks with predicted high Robinhood interest, and Panel B reports results for the effect of traditional brokerage platform outages on stocks with predicted high aggregate retail interest. 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.

| | Platform Outages | | | | Pseudo Outages | | | |
|---|---|---|---|---|---|---|---|---|
| | Quoted Spread | Effective Spread | Realized Spread | Price Impact | Quoted Spread | Effective Spread | Realized Spread | Price Impact |
| **Panel A: Stocks with High Expected Robinhood Trading during Robinhood Platform Outages** | | | | | | | | |
| $Robinhood_{i,d-1} \times Outage_t$ | -0.718*** | -0.983*** | -0.465** | -0.413*** | -0.711 | -0.383 | 0.118 | -0.482 |
| | (-2.737) | (-2.636) | (-2.287) | (-2.639) | (-1.372) | (-1.151) | (0.377) | (-1.217) |
| $Robinhood_{i,d-1}$ | -0.23* | -0.558** | 0.209* | 0.153*** | -1.036* | -0.099 | 0.101 | -0.088 |
| | (-1.843) | (-2.096) | (1.731) | (1.329) | (-1.917) | (-0.244) | (0.232) | (-0.199) |
| $Outage_t$ | -0.348 | -0.621 | -0.253 | -0.517 | 0.576 | 0.358 | 0.379 | 0.108 |
| | (-0.081) | (-0.179) | (-0.136) | (-0.284) | (0.962) | (0.702) | (0.761) | (0.134) |
| Firm Clusters | 1964 | 1964 | 1964 | 1964 | 1964 | 1964 | 1964 | 1964 |
| Δ R-squared (%) | 0.225 | 0.094 | 0.118 | 0.032 | 0.018 | 0.015 | 0.027 | 0.033 |
| **Panel B: Stocks with High Expected Aggregate Retail Trading during Traditional Broker Outages** | | | | | | | | |
| $Retail_{i,d-1} \times Outage_t$ | 0.381** | 0.388*** | 0.186** | 0.202 | 0.044 | -0.002 | 0.049 | -0.052 |
| | (2.363) | (2.857) | (2.287) | (1.564) | (0.117) | (-0.009) | (0.182) | (-0.325) |
| $Retail_{i,d-1}$ | -1.404* | -0.528 | -1.66* | 1.146* | -1.043** | -0.407*** | -1.106*** | 0.699*** |
| | (-1.744) | (-1.381) | (-1.833) | (1.736) | (-2.483) | (-2.851) | (-3.236) | (2.676) |
| $Outage_t$ | -0.606 | -0.448 | -0.243 | -0.188 | -0.09 | -0.018 | -0.047 | 0.029 |
| | (-0.267) | (-0.262) | (-0.279) | (-0.195) | (-0.168) | (-0.046) | (-0.158) | (0.096) |
| Firm Clusters | 1964 | 1964 | 1964 | 1964 | 1964 | 1964 | 1964 | 1964 |
| Δ R-squared (%) | 0.066 | 0.013 | 0.046 | 0.025 | 0.139 | 0.027 | 0.038 | 0.015 |

**Table 8. Retail Broker Platform Outages and Stock Return Volatility**

The table reports the effects of retail brokerage outages on a measure of stock return volatility for stocks with high retail interest. The sample consists of 5-minute intervals, *t*, for each firm *i* during the window on day *d* when the retail brokerage 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 outage sample is the actual time window in which the brokerage 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 5 and Section 4. Panel A represents the effect of Robinhood platform outages on stocks with predicted high Robinhood interest, and Panel B reports results for the effect of traditional brokerage platform outages on stocks with predicted high aggregate retail interest. 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: Robinhood Platform Outages and Stocks with High Expected Robinhood Trading

| | Robinhood Outages | Pseudo Outages |
|---|---|---|
| $Robinhood_{i,d-1} \times Outage_t$ | -0.250** | -0.121 |
| | (-2.219) | (-0.407) |
| $Robinhood_{i,d-1}$ | 0.238* | 0.317* |
| | (1.934) | (1.846) |
| $Outage_t$ | -0.158 | -0.268 |
| | (-0.689) | (-0.500) |
| | | |
| Firm Clusters | 1,964 | 1,964 |
| Δ R-squared (%) | 0.038 | 0.017 |

Panel B: Traditional Brokers Platform Outages and Stocks with High Expected Aggregate Retail Trading

| | Traditional Brokers Outages | Pseudo Outages |
|---|---|---|
| $Retail_{i,d-1} \times Outage_t$ | 0.370** | 0.057 |
| | (2.081) | (0.424) |
| $Retail_{i,d-1}$ | 1.383*** | 0.582*** |
| | (3.96) | (4.032) |
| $Outage_t$ | -0.321 | -0.093 |
| | (-0.192) | (-0.241) |
| | | |
| Firm Clusters | 1,964 | 1,964 |
| Δ R-squared (%) | 0.158 | 0.067 |

**Table 9. Retail Broker Platform Outages and Market Quality – Robustness Checks**

The table reports robustness checks of the results in Tables 5-8. For brevity, each panel reports only the interaction term that captures the effects of outages on stocks with high expected trading. *Robinhood* (*Retail*) denotes specifications in which treated firms are those with high expected Robinhood (Aggregate Retail) trading. Panel A excludes stocks with an increase of 20% or more in WallStreetBets Mentions on the outage date. Panel B excludes outages that begin prior to 9:45 AM EST. Panel C excludes outages in March 2020. Panel D considers a benchmark 6-10 days before the outage. Panel E excludes stocks in the lowest quintile of retail interest. Panel F matches the event periods more closely to the pseudo-event periods. Panel G uses expected aggregate retail trading for the Robinhood outages and expected Robinhood trading for the traditional broker outages.

| | Trading Volume | Trading Intensity | Agg. Retail Volume | Trade Imbalance | Depth Imbalance | Quoted Spread | Effective Spread | Realized Spread | Price Impact | Volatility |
|---|---|---|---|---|---|---|---|---|---|---|
| Panel A: Exclude Firm-Outage Events with a 20% Spike in WallStreetBets Mentions | | | | | | | | | | |
| $Robinhood_{i,d-1}$ × $RH\ Outage_t$ | -0.027* | -0.024* | -0.121*** | -2.338*** | -2.519*** | -0.108*** | -0.229*** | -0.135*** | -0.084** | -0.121*** |
| | (-1.761) | (-1.893) | (-2.997) | (-3.017) | (-3.695) | (-2.844) | (-3.388) | (-2.957) | (-2.193) | (-3.238) |
| $Retail_{i,d-1}$ × $Other\ Outage_t$ | -0.019** | -0.008* | -0.104** | 6.135** | 2.296*** | 0.025** | 0.168*** | 0.241*** | 0.08* | 0.256*** |
| | (-2.344) | (-1.77) | (-2.425) | (2.181) | (3.186) | (2.084) | (3.330) | (3.465) | (1.757) | (2.671) |
| Panel B: Exclude Platform Outages that begin before 10:00 AM | | | | | | | | | | |
| $Robinhood_{i,d-1}$ × $RH\ Outage_t$ | -0.013*** | -0.012* | -0.037** | -5.145** | -4.108*** | -0.141** | -0.189*** | -0.193*** | -0.127* | -0.153*** |
| | (-2.861) | (-1.748) | (-2.484) | (-2.385) | (-3.332) | (-2.103) | (-3.184) | (-2.772) | (-1.764) | (-2.798) |
| $Retail_{i,d-1}$ × $Other\ Outage_t$ | -0.012* | -0.007* | -0.103** | 5.499** | 2.395** | 0.187** | 0.17*** | 0.115** | 0.046** | 0.096* |
| | (-1.919) | (-1.861) | (-2.359) | (2.143) | (2.129) | (2.299) | (2.639) | (2.421) | (2.354) | (1.757) |
| Panel C: Exclude All Platform Outages in March 2020 | | | | | | | | | | |
| $Robinhood_{i,d-1}$ × $RH\ Outage_t$ | -0.018* | -0.016* | -0.086*** | -4.966* | -8.063*** | -0.273** | -0.223* | -0.129* | -0.152* | -0.116*** |
| | (-1.771) | (-1.789) | (-2.888) | (-1.803) | (-3.164) | (-2.734) | (-1.763) | (-1.708) | (-1.678) | (-3.482) |
| $Retail_{i,d-1}$ × $Other\ Outage_t$ | -0.090* | -0.005* | -0.138** | 4.79*** | 4.592*** | 0.157* | 0.139*** | 0.281*** | 0.05** | 0.183* |
| | (-1.887) | (-1.742) | (-2.436) | (3.048) | (3.143) | (1.743) | (2.738) | (3.801) | (1.992) | (1.765) |
| Panel D: Measure Benchmark Control Period 6 to 10 Days before Platform Outage (Instead of 1 to 5 Days before) | | | | | | | | | | |
| $Robinhood_{i,d-1}$ × $RH\ Outage_t$ | -0.011** | -0.011* | -0.16** | -3.222*** | -5.784*** | -0.218*** | -0.219* | -0.18** | -0.206*** | -0.212*** |
| | (-2.102) | (-1.747) | (-2.079) | (-3.44) | (-2.8) | (-3.2) | (-1.875) | (-2.231) | (-3.099) | (-2.692) |
| $Retail_{i,d-1}$ × $Other\ Outage_t$ | -0.018* | -0.015* | -0.167*** | 7.367** | 4.587*** | 0.22*** | 0.186** | 0.171*** | 0.2** | 0.204** |
| | (-1.721) | (-1.905) | (-2.837) | (2.032) | (3.335) | (3.222) | (2.251) | (2.721) | (2.298) | (2.249) |

**Table 9. Retail Broker Platform Outages and Market Quality – Robustness Checks (continued)**

| | Trading Volume | Trading Intensity | Agg. Retail Volume | Trade Imbalance | Depth Imbalance | Quoted Spread | Effective Spread | Realized Spread | Price Impact | Volatility |
|---|---|---|---|---|---|---|---|---|---|---|
| Panel E: Exclude Firm-Outage events with Retail Interest in the Lowest Quintile | | | | | | | | | | |
| *$Robinhood_{i,d-1}$ × $RH\ Outage_t$* | -0.044** | -0.016* | -0.113* | -7.712* | -10.114** | -0.314*** | -0.195*** | -0.124*** | -0.073*** | -0.113** |
| | (-2.213) | (-1.873 | (-1.821) | (-2.385) | (-2.213) | (-2.956) | (-2.314) | (-2.645) | (-3.129) | (-2.374) |
| *$Retail_{i,d-1}$ × $Other\ Outage_t$* | -0.027* | -0.028* | -0.188* | 4.895*** | 7.746*** | 0.195*** | 0.276* | 0.251** | 0.219*** | 0.224** |
| | (-1.813) | (-1.764) | (-2.114) | (2.943) | (3.218) | (3.134) | (1.893) | (2.101) | (2.820) | (2.380) |
| Panel F: Limit Outage Observations to Match Pseudo Outage Observations | | | | | | | | | | |
| *$Robinhood_{i,d-1}$ × $RH\ Outage_t$* | -0.041* | -0.010** | -0.061* | -15.322** | -22.785** | -0.081** | -0.348** | -0.123* | -0.058* | -0.129** |
| | (-1.912) | (-2.140) | (-1.725) | (-2.449) | (-2.194) | (-2.043) | (-2.229) | (-1.914) | (-1.686) | (-2.089) |
| *$Retail_{i,d-1}$ × $Other\ Outage_t$* | -0.022* | -0.029** | -0.023** | 8.943** | 14.803** | 0.165* | 0.346** | 0.156** | 0.136* | 0.216** |
| | (-1.734) | (-2.003) | (-2.213) | (2.063) | (2.498) | (1.894) | (2.354) | (2.499) | (1.877) | (2.309) |
| Panel G: Alternative Expected Trading Measures | | | | | | | | | | |
| *$Retail_{i,d-1}$ × $RH\ Outage_t$* | -0.011** | -0.020** | -0.035*** | -14.231* | -32.603*** | -1.174*** | -0.624*** | -0.439** | -0.223** | -0.29*** |
| | (-2.414) | (-2.166) | (-3.212) | (-1.812) | (-3.461) | (-2.747) | (-2.599) | (-2.390) | (-2.159) | (-2.783) |
| *$Robinhd_{i,d-1}$ × $Other\ Outage_t$* | -0.043** | -0.036* | -0.071** | 12.139** | 20.311*** | 0.643** | 0.565** | 0.29* | 0.172 | 0.214*** |
| | (-2.361) | (-1.755) | (-2.179) | (2.123) | (3.192) | (2.225) | (2.366) | (1.721) | (0.524) | (2.648) |

**Table 10. Outages and Quoting by HFTs that have Order Flow Arrangements with the Broker Experiencing the Outage**

The table reports the effects of retail brokerage outages on affiliated- and unaffiliated-market maker spreads and inventory imbalance for stocks with high retail investor interest. The dependent variable in each specification is a measure of either market maker spreads or depth imbalance, which are computed for the subset of orders with MPID attributions, partitioned by market makers with and without payment for order flow arrangements with the broker experiencing the outage. These variables are described in more detail in Section 2 and Appendix A. The sample consists of 5-minute intervals, $t$, for each firm $i$ during the window on day $d$ when the broker 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 outage sample is the actual time window in which the brokerage 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 5. Panel A represents the effect of Robinhood platform outages on stocks with predicted high Robinhood interest, and Panel B reports results for the effect of traditional brokerage platform outages on stocks with predicted high aggregate retail interest. 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: Stocks with High Expected Robinhood Trading during Robinhood Platform Outages

| | Robinhood Outages | | | | Pseudo Outages | | | |
|---|---|---|---|---|---|---|---|---|
| | Affiliated Market Maker Spreads | Other Market Maker Spreads | Affiliated Market Maker Depth Imbal. | Other Market Maker Depth Imbalance | Affiliated Market Maker Spreads | Other Market Maker Spreads | Affiliated Market Maker Depth Imbal. | Other Market Maker Depth Imbalance |
| $Robinhood_{i,d\text{-}1} \times Outage_t$ | -4.544*** | -2.895 | -19.962*** | 4.669 | -1.37 | -10.169 | -0.984 | 4.432 |
| | (-3.723) | (-0.997) | (-2.852) | (0.398) | (-1.639) | (-0.93) | (-0.249) | (0.342) |
| $Robinhood_{i,d\text{-}1}$ | -2.693** | -0.667 | 15.998** | 1.126 | -0.829** | 1.185 | 0.039** | -3.518 |
| | (-2.138) | (-1.217) | (2.441) | (0.158) | (-2.335) | (-1.107) | (2.017) | (-0.506) |
| $Outage_t$ | -0.795 | 0.893 | 6.234 | -7.519 | 0.786 | 5.599 | 1.617 | 4.558 |
| | (-0.49) | (0.341) | (0.442) | (-0.409) | (1.07) | (0.697) | (0.441) | (0.37) |
| Firm Clusters | 1,964 | 1,964 | 1,964 | 1,964 | 1,964 | 1,964 | 1,964 | 1,964 |
| Δ R-Squared (%) | 2.434 | 4.553 | 1.427 | 0.216 | 6.650 | 3.072 | 0.431 | 0.102 |

**Table 10. Outages and Quoting by HFTs that have Order Flow Arrangements with the Broker Experiencing the Outage (continued)**

Panel B: Stocks with High Expected Aggregate Retail Trading during Outages at other Brokers

| | Traditional Broker Outages | | | | Pseudo Outages | | | |
|---|---|---|---|---|---|---|---|---|
| | Affiliated Market Maker Spreads | Other Market Maker Spreads | Affiliated Market Maker Depth Imbal. | Other Market Maker Depth Imbalance | Affiliated Market Maker Spreads | Other Market Maker Spreads | Affiliated Market Maker Depth Imbal. | Other Market Maker Depth Imbalance |
| $Retail_{i,d\text{-}1}$ × $Outage_t$ | 4.279*** | -0.323 | 6.681** | -7.972 | -0.266 | -0.613 | -6.703 | 2.907 |
| | (3.423) | (-1.265) | (2.526) | (-0.685) | (-0.518) | (-0.599) | (-0.753) | (0.312) |
| $Retail_{i,d\text{-}1}$ | -1.802** | -0.496 | -6.725 | -9.71* | -0.358 | -2.894 | 2.845 | -10.781* |
| | (-1.998) | (-1.487) | (-1.561) | (-1.676) | (-1.189) | (-1.396) | (0.525) | (-1.83) |
| $Outage_t$ | -0.128 | -1.603 | -7.142 | -11.14 | 1.105 | -0.066 | -1.529 | -4.729 |
| | (-0.097) | (-0.114) | (-1.419) | (-0.834) | (1.111) | (-0.082) | (-0.22) | (-0.562) |
| Firm Clusters | 1,964 | 1,964 | 1,964 | 1,964 | 1,964 | 1,964 | 1,964 | 1,964 |
| Δ R-Squared (%) | 2.583 | 2.966 | 1.125 | 0.531 | 2.561 | 1.914 | 0.128 | 0.214 |

# Internet Appendix

**Table IA1. Affiliated Nasdaq Market Makers**
Panel A lists the Nasdaq dealers with payment for order flow arrangements with retail brokers during the January 2019 to June 2021 sample period, and Panel B lists the remaining set of (Nasdaq and FINRA member) market makers.

Panel A: Retail-Affiliated Market Participant IDs

| MPID | Name | MPID | Name |
|---|---|---|---|
| CTDL | Citadel Derivatives Group LLC | SOHO | Two Sigma Securities LLC |
| CDRG | Citadel Securities LLC | TSSM | Two Sigma Securities LLC |
| ETMM | G1 Execution Services LLC | UBSS | UBS Securities LLC (Non-Robinhood) |
| JSCA | Jane Street Capital LLC (E-Trade Only) | VIRT | Virtu Americas LLC |
| NITE | VIRTU Americas LLC | WSEA | Wolverine Securities LLC (Robinhood Only) |
| OHOS | 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 |
| JANY | Janney Montgomery Scott Inc. | TLSA | TRADELINK 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. Retail Broker FAQ Webpage Categories among Website Visitors in 2020**

The table presents website usage patterns of Robinhood and 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 IA3. Retail Broker Platform Outages and Market Quality – Individual Broker Evidence**

The repeats the analysis in Table 9 for each traditional brokerage firm separately. Panel A reports the results for Schwab outages, Panel B analyzes E-Trade outages, and Panel C studies TD Ameritrade outages.

| | Trading Volume | Trading Intensity | Agg. Retail Volume | Trade Imbalance | Depth Imbalance | Quoted Spread | Effective Spread | Realized Spread | Price Impact | Volatility |
|---|---|---|---|---|---|---|---|---|---|---|
| Panel A: Charles Schwab Outages | | | | | | | | | | |
| $Retail_{i,d} \times Outage_t$ | -0.007* | -0.005* | -0.095* | 8.608** | 6.931** | 0.135 | 0.167** | 0.16** | 0.058* | 0.047** |
| | (-1.687) | (-1.831) | (-1.951) | (2.012) | (2.482) | (1.247) | (2.184) | (2.137) | (1.852) | (2.023) |
| Panel B: E-Trade Outages | | | | | | | | | | |
| $Retail_{i,d} \times Outage_t$ | -0.008* | -0.003 | -0.007* | 8.333* | 6.879** | 0.071* | 0.112** | 0.138* | 0.077*** | 0.054* |
| | (-1.707) | (-1.453) | (-1.883) | (1.741) | (2.119) | (1.809) | (2.180) | (1.879) | (2.819) | (1.899) |
| Panel C: TD Ameritrade Outages | | | | | | | | | | |
| $Retail_{i,d} \times Outage_t$ | -0.009** | -0.008* | -0.119** | 2.139* | 2.022** | 0.112* | 0.101* | 0.169** | 0.116** | 0.156* |
| | (-2.104) | (-1.752) | (-2.390) | (1.775) | (2.385) | (1.905) | (1.852) | (2.163) | (2.386) | (1.776) |