The Public Availability of Robinhood Holdings Data and Market Quality

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Abstract

This paper examines the effect of the public availability of information on the number of Robinhood users holding individual stocks on market quality. We use the shutdown of public access to the Robinhood users' holdings data as a quasi-natural experiment. The shutdown improves stock liquidity and reduces intraday volatility on the one hand but diminishes informational efficiency on the other hand. These effects are more pronounced for stocks of higher popularity among Robinhood investors. Moreover, these seemingly contrasting effects can be well explained by algorithmic trading activities of institutional investors who are unable to access to the data after the shutdown.

Keywords: Retail Investor, Market Quality, Order Flow Data, Robinhood

JAL Classification: G11, G12, G14, G23

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1. Introduction

Regulators and academic researchers have been debating on whether and to what extent the information on order flows in stock markets should be available to the public (e.g., Meling, 2021; SEC, 2009; Yang & Zhu, 2020). Theoretical and empirical studies do not reach a consensus on the impact of this information on market quality. One possible explanation for this ambiguity is that the information can be useful in different trading strategies which have different effects on market quality (Beason & Wahal, 2020; Hagströmer & Nordén, 2013). [1]

This paper addresses the open question of the effect of order flow information on market quality by empirically examining the public availability of retail order flow data. In mid-2018, Robinhood, a commission-free retail brokerage firm, introduced an Application Programming Interface (API) that enables the public to obtain the number of specific accounts that hold a particular stock at any moment. The number of accounts coming from API enable us to measure trading activities of Robinhood users. None of other brokers have ever provided this feature. There are concerns that sophisticated traders incorporate the data into their trading decisions, since such data provides insights into the behaviours of not only investors using the Robinhood's trading platform but also other retail investors. [2] Robinhood suddenly turned off the API on August 13,

[1] For instance, back-runners are likely to feed their algorithm with order flow data in order to trade in the direction of the fundamental information and earn profits (Korajczyk & Murphy, 2019; Yang & Zhu, 2020). This generally increases trading costs and decreases the gains of informed investors. On the other hand, informed traders such as large institutions can also use order flow data to avoid their trading motives being detected by the back-runners (Beason & Wahal, 2020).

[2] https://www.bloomberg.com/news/articles/2020-07-23/hedge-funds-approach-robintrack-to-keep-eyes-on-tiny-investors.

2020,[3] which provides an environment for quasi-natural experiment to answer our research question, as the discontinuity of data provision can be considered as an exogenous shock.[4]

We start our investigation with testing the difference in market quality measured over five trading days before and after the shutdown of API.[5] We find that stock liquidity increases and intraday volatility in stock returns falls, while informational efficiency decreases, following the shutdown. The changes in these market quality measures across the shutdown remain strongly significant, even after controlling for multiple variables that might affect market quality. Our findings partly explain the positive effects of Robinhood platform outages on market quality in Eaton et al., (2021), because the outages not only make Robinhood investors unable to trade but also prevent other market participants from using Robinhood data.

If these effects of the API shutdown are driven by the fact that some market participants are unable to access to the data after the shutdown, such effects should be stronger among stocks for which the data is more useful. We use average Robinhood activities in the five trading days prior to the shutdown as proxy for the usefulness of Robinhood data. Our results confirm that the shutdown has significantly stronger effects on market quality for stocks with higher Robinhood activities.

The next natural question is why the public access to Robinhood data such seemingly contradicting effects on market quality has, i.e., improving liquidity and reducing volatility vs.

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[3] Robinhood states that the reason for the turning off is that the data "can be reported by third parties in a way that could be misconstrued or misunderstood", and "importantly it is not representative of how our customer base uses Robinhood." According to Casey Primozic, the Robintrack website creator, Robinhood argues that the data is reported in a way that "paints Robinhood as being full of day traders when they say most of their users are 'buy-and-hold' investors. See, https://www.bloomberg.com/news/articles/2020-08-08/robintrack-chronicler-of-day-trader-stock-demand-to-shut-down.

[4] "Steve Cohen's Point72 and other hedge funds are sending urgent requests to find a replacement after Robinhood's data on hot stock trades suddenly went dark".https://www.businessinsider.com/point72-contacts-other-investing-apps-after-robinhood-data-taken-down-2020-8?r=AU&IR=T

[5] The five days prior to the shutdown include August 13, 2020, for ease of exposition.

spoiling informational efficiency. To answer this question, we investigate who use this data prior to the API shutdown but are unable to access the relevant information afterwards. We argue that Robinhood data, because of its high-frequency nature, presumably mainly used by trading algorithms rather than humans. The two major users of trading algorithms are high-frequency market making firms and large institutional investors (Beason & Wahal, 2020; Hagströmer & Nordén, 2013; O'Hara et al., 2014). Commission-free brokerage firms like Robinhood make revenue through selling their clients' order flows to high-frequency market making firms. These firms still have the access to the information of retail order flows even after the Robinhood close the public access to API. Thus, high-frequency market makers' information set is unlikely to be severely affected by the discontinuity of API.

On the other hand, large institutions are widely considered as informed traders as they often trading on their private information of fundamentals (e.g., Chiang et al., 2010; Hendershott et al., 2015; Yan & Zhang, 2009). Data on retail order flows is highly valuable for them to choose proper trading strategies to hide their trading motives, thus reducing their trading costs (O'Hara et al., 2014). Institutional algorithms often break a parent order into hundreds of child orders to reduce their market impacts (Beason & Wahal, 2020). Following the shutdown of the API, these institutional investors no longer have the access to the Robinhood data on retail order flows, which has two implications. First, with less observability of retail order flows, they would trade less aggressively on their private information (Yang & Zhu, 2020), which leads to less fundamental information timely reflected in price and lowers informational efficiency. Second, the reduced aggressiveness of privately informed trading should lower adverse selection, which allows market makers to narrow the bid-ask spreads or improve stock liquidity since bid-ask spread is inversely related to liquidity.

To test the abovementioned conjectures, we employ the termination of public access to the Robinhood data as an instrument for alteration of the algorithmic trading of institutional investors. Consistent with the conjectures, the termination is associated with lower institutional algorithmic trading. More importantly, the part of institutional algorithmic trading that is affected by the event is negatively associated with stock liquidity but positively associated with informational efficiency. We also find that this part of trading is negatively related to intraday volatility, which can be explained by back-running trading activities in the markets. Back-runners often monitor order flows to infer informed orders so that they can trade in the same direction as these orders and make profits (Yang & Zhu, 2020). Thus, back-running might increase inventory-holding risk for market makers, which is likely to make them revise quotes more often and create excess short-term (intraday) volatility. With the reduction of informed trading by institutions after the shutdown of API, back-running activities may also drop, which in turn leads to decrease in intraday volatility. In sum, our analysis provides empirical evidence supporting the idea that the shutdown reduces informed trading by institutions and consequently generates observed impacts on market quality.

An alternative channel driving the observed effects is through sophisticated traders who infer fundamental information in Robinhood holdings data. The shutdown of the data checks trading of those traders from such back-running behavior, which reduces adverse selection costs but delays the incorporation of information into stock prices. To test this channel, we first estimate Fama & MacBeth (1973) regressions of future market-adjusted returns on Robinhood trading activities and other well-known predictors including aggregate retail order imbalance. The results show that Robinhood holdings data contains useful information incremental to the other predictors in predicting future returns. If that information is exploited by sophisticated traders, we should observe an increase in retail trading profits after the API shutdown, because other traders can no longer extract information in their order flow. We find a significant improvement in retail profits only at the five-day horizon and in stocks with high Robinhood activities.

We conduct various test to check the robustness of our findings. We replicate the main results using stock liquidity measured at various short time horizons. We also consider different proxies for Robinhood activities and institutional algorithmic trading. The replicated results are qualitatively similar to our main findings. We further examine the robustness of our findings by estimating the effects of two pseudo-events, one before and one after the actual event, and confirm that these pseudo-events have no significant effects on market quality.

Our study contributes to several areas of financial studies. First, prior literature on the effect of order flow information on market quality primarily focuses on pre-trade or post-trade transparency, i.e., the extent to which market participants can observe trader identities. Theories on pre-trade transparency provides mixed predictions. While some theories predict that pre-trade transparency improves liquidity by reducing information asymmetry (e.g., Pagano & Röell, 1996), others predict it is harmful to liquidity because it makes informed traders switch from using limit orders to market orders (e.g, Boulatov & George, 2013; Rindi, 2008). Theoretical studies on post-trade transparency provide generally consistent predictions. For instance, both models developed by Huddart et al. (2001) and Yang & Zhu (2020) predict that post-trade transparency enhances stock liquidity by alleviating market makers' adverse selection risk. Empirical work on market transparency employs stock market regulation reforms that remove pre- or post- trader identities as exogenous shocks to study the causal effect of transparency variation on stock liquidity. Comerton-Forde & Tang (2009) and Foucault et al. (2007) demonstrate that pre-trade anonymity improves liquidity by encouraging informed traders to use limit orders. While Friederich & Payne (2014), Dennis & Sandås (2020), and Meling (2021) provide evidence of post-trade anonymity improving stock liquidity, Pham et al. (2016) document a negative effect on liquidity but a positive effect on market efficiency.

In this family of market transparency literature, our paper examines a unique event that shuts down the public access to retail order flow data. To the best of our knowledge, it is the first attempt to provide evidence that institutional investors might use information on retail order flows for their execution optimization, as well as its implication for market quality. Our paper also complements the works of Yang & Zhu (2020) and Beason & Wahal (2020). Yang & Zhu (2020) models the interaction between fundamentally informed investors and back-runners. They show that the practice of payment for retail order flows enables back-runners to earn large profits at the expense of informed institutions. Beason & Wahal (2020) provide empirical evidence on how informed institutions use child orders to optimize their executions.

Our idea that Robinhood holdings data is used by sophisticated traders is related to the literature on trading based on non-fundamental information. The literature generally finds a negative effect of this trading on price efficiency. There is evidence that predatory algorithmic traders adopting opportunistic trading strategies such as order anticipation and momentum ignition, which in turn increase intraday volatility and decreasing price efficiency (Boehmer et al., 2020; Hagströmer & Nordén, 2013; Kirilenko et al., 2017). Consistently, Li, Yin and Jing (2020) demonstrate that program trading causes excessive daily return co-movement that is unrelated to fundamental information and in turn lowers price efficiency.

Our paper also contributes to the growing literature on commission-free retail investors whose behaviour significantly differ from traditional retail investors. Barber et al. (2021) find that simplified display of information in the Robinhood trading app is linked to herding episodes in the users, which can impact pricing of stocks. Welch (2021) shows that Robinhood investors tend to hold stocks with large persistent past volume and do not underperform based on standard academic benchmark models, which is contrary to common beliefs. Ozik et al. (2021) find that retail trading reduces illiquidity during the COVID-19 pandemic period. Our paper documents an unintentional effect of a unique feature of the Robinhood trading platform on market quality.

The rest of the paper is organized as follows. Section 2 outlines our data sources and describes variables used in the paper. Section 3 presents the baseline findings as well as compares Robinhood stocks with non-Robinhood stocks to consolidate the findings. Section 4 investigates the force that is likely to drive the relationship between the shutdown of API and market quality, while Section 5 conducts various tests to verify the robustness of this relationship. Section 6 concludes the paper.

2. Data and Variables

2.1. Data sources

We collect data from multiple sources for our analysis. Trades and quotes data are collected from the NYSE Trade and Quote (TAQ) databases. Data on daily returns and closing prices are collected from the Center for Research in Securities Prices (CRSP) database.

We obtain Robinhood users' holdings data from the Robintrack, which is a website that started scraping the number of unique Robinhood users holding each stock at an hourly interval from May 2018 and stopped on August 13, 2020 when the Robinhood API was shutdown. We exclude observations reported outside the trading hours. The Robintrack dataset is used in recent studies on Robinhood investors (e.g., Barber et al., 2021; Welch, 2021).

We scrape posts and comments from the WallStreetBets forums on the Reddit social media platform using the Pushift Reddit API.[6] WallStreetBets has become the largest stock trading forum in the world with over ten million members. WallStreetBets members consist mainly of young and inexperienced investors who usually use zero-comission online trading platforms such as Robinhood.[7] We calculate the number of times the stock is mentioned in the Reddit's WallStreetBets message board (r/wallstrettbets) following Eaton et al. (2021) and Hu et al. (2021). Hu et al. (2021) find that Reddit traffic is strongly associated with Robinhood trading activities.

2.2. Market quality measures

Our main stock liquidity measure is the effective spread,

$$ESpread_t = 2q\left[\frac{p_t - m_t}{m_t}\right],$$

where p_t is the transacted price, m_t is the bid-ask mid-quote price, t is the time of the trade and q is the indicator for the direction of the trade (1 for a buyer-initiated trade and -1 for a seller-initiated trade). Trade directions are identified using the Lee & Ready (1991) algorithm. For robustness, we use several alternative liquidity measures used in prior studies, including quoted spread, realized spread, price impact, and market depth:

$$QSpread_t = 2[Ask_t - Bid_t]$$

$$RSpread_t = 2q\left[\frac{p_t - m_{t+5}}{m_t}\right]$$

$$PriceImpact_t = 2q\left[\frac{m_{t+5} - m_t}{m_t}\right]$$

$$Depth_t = BidDepth_t + AskDepth_t$$

[6] https://github.com/pushshift/api

[7] https://www.forbes.com/sites/petertchir/2021/01/30/what-do-we-know-about-robinhood--wallstreetbets/

where Ask_t and Bid_t are the best prevailing ask and bid quotes at the time of the trade, m_{t+5} is the mid-quote price five minutes after the trade, and $BidDepth_t$ and $AskDepth_t$ are the numbers of shares available at the best bid and ask quotes. For each stock-day, effective spread, realized spread, and price impact are volume-weighted averaged, while the quoted spread and depth are time-weighted averaged. Higher effective spread, realized spread, and price impact are associated with higher transaction costs and lower liquidity. Meanwhile, higher market depth is associated with better liquidity.

We measure intraday volatility of a stock on a day by the standard deviations of mid-quote returns on the stock calculated at the 10-second and 60-second horizons; namely, $SD10$ and $SD60$, respectively. These measures capture stock return volatility induced by microstructure factors such as market makers' adverse selection or inventory holding risk, rather than volatility in the stock fundamentals (Glosten & Milgrom, 1985; Ho & Stoll, 1981). To attenuate the concern that these measures might be correlated with volatility in stock fundamentals, we include daily volatility as a control variable in the regression analysis.

For informational efficiency, we consider three measures: absolute autocorrelations of mid-quote return at 10-second and 60-second intervals. i.e., $Autocorr10$ and $Autocorr60$, respectively, and the variance ratio of the two returns, VR. More specifically, the absolute autocorrelations are given by:

$$Autocorr10 = \left|Corr\left(r_{10,\tau}, r_{10,\tau-1}\right)\right|,$$

$$Autocorr60 = \left|Corr\left(r_{60,\tau}, r_{60,\tau-1}\right)\right|,$$

where $r_{10,\tau}$ and $r_{60,\tau}$ denote the mid-quote returns for the τth intervals of lengths 10 seconds and 60 seconds, respectively, for a particular stock-day. Larger absolute return autocorrelations indicate higher short-term return predictability which is consistent with lower informational efficiency (Chordia et al., 2008; Hendershott & Jones, 2005). The variance ratio is calculated as:

$$VR = \left|\frac{Var_{60}}{6 \times Var_{10}} - 1\right|,$$

where Var_{60} and Var_{10} are variances in 60-second and 10-second mid-quote returns, respectively. This measure captures how much a price process deviates from a random walk, which is consistent with an efficient market (Lo & MacKinlay, 1988). Thus, higher variance ratio indicates lower informational efficiency.

2.3. Robinhood activity proxies

Our proxies for Robinhood activities are similar to those used in Eaton et al. (2021). Our main proxy is Robinhood absolute user change, RH. For each stock, we calculate the hourly absolute change in the number of Robinhood users who hold the stock. Then we average this number across the five days prior to Robinhood shutting its API down on August 13, 2020.

As a robustness check, we use a second proxy for Robinhood activities that is Reddit mentions, $Reddit$. $Reddit$ is defined as the number of posts and comments mentioning the stock on Reddit's Wallstreetbets forum over the same five-day period. We identify whether a post or comment mentions a stock by identifying whether it contains the stock's ticker.

2.4. Institutional algorithmic trading proxies

Our main proxy for institutional algorithmic trading activities is $OddLot$, which is defined as the percentage of daily trading volume attributed to odd-lot trades (O'Hara et al., 2014). An odd-lot trade is a trade of less than 100 shares. Since odd-lot trades are not included in the consolidated tape that is disseminated to the public in real-time, they are often used by informed investors to hide their information, thus reducing market impact of their trades. The Securities and Exchange Commission (SEC) adopts odd-lot trades as a proxy for algorithmic trading. Indeed, O'Hara et al. (2014) find that odd-lot trades are responsible for 35% of price discovery. This suggests that $OddLot$ mainly captures algorithmic trading activities of informed institutional investors rather than the uninformed types of algorithmic traders such as high-frequency market makers.

For robustness check, we proxy institutional algorithmic trading by an alternative measure, ISO, which is defined as the percentage of daily trading volume attributed to intermarket sweep orders (ISOs). An ISO is an order that sweep across exchange to pick up as many shares as possible using algorithms. There is evidence that ISOs are mainly used by informed institutions to hide trading intentions (Chakravarty et al., 2012).

2.5. Control variables

To control for confounding factors that may affect market quality, we include in our regression analysis several control variables that are related to market quality but unlikely to be related to information shocks (e.g., Foley & Putniņš, 2016; Hendershott et al., 2011). The first control is daily volatility, $DVolatility$, which is measured as the standard deviation of daily stock return in the previous 20 trading days. Daily volatility should capture volatility in a stock’s fundamental rather than volatility due to microstructure factors. The second control variable is turnover, $Turnover$, which is the daily trading volume of a stock scaled by its market capitalization. The other control variables are natural logarithm of market capitalization, $LogMktCap$, and the inverse of price, $InvPrice$.

2.6. Sample selection and univariate tests

The sample period covers ten trading days around the time of the event (23:59:59, August 13, 2020) to include one full trading week before and one after the event. This helps minimizing the impact of the day-of-the-week effect on our estimates (Birru, 2018). We do not extend the sample period longer than one week around the event to avoid the impact of confounding factors. For example, if the period is longer, market participants might have sufficient time to find another data source that contains similar information as the Robinhood data,[8] which may contaminate our estimates for the causal effects of the API shutdown.

Our sample includes common stocks (i.e., stocks with share code 10 or 11) publicly traded on the NYSE, AMEX, or NASDAQ. Following prior studies, we exclude "penny" stocks, which are the stocks whose prices fall below $1 on any day in the sample period. This screen results in 3,011 individual stocks and 30,110 stock-day observations in the sample. All continuous variables are winsorized at the 0.5% and 99.5% within each day to reduce the impact of outliers.

Panels A, B, and C in Table 1 display nonparametric tests examining the variation of market quality due to Robinhood closing the public access to its API. Columns 1 to 3 report mean, median and standard deviation of the variables prior to Robinhood shuts its API down while Columns 4 to 6 report the numbers after the shutdown. Columns 7 and 8 show the differences because of the shutdown and the t-statistics of the differences.

Insert Table 1 here

As shown in Panel A of table 1, after the API shutdown, effective spread, quoted spread, realized spread, and price impacts are significantly smaller, while market depth is significantly larger. These changes are consistent with a more liquid market. The difference appears to be weaker for quoted spread and market depth. These two measures are arguably poorer measures of stock liquidity, because they rely on the best bid and ask quotes, while in modern markets, a bulk of trades are executed within or beyond the best quotes (Chordia et al., 2001). Quoted spread is

[8] For example, several hedge funds urgently contacted other trading apps to request for a replacement for Robinhood data, after it was turned off API. See https://www.businessinsider.com/point72-contacts-other-investing-apps-after-robinhood-data-taken-down-2020-8?r=AU&IR=T

especially an inaccurate measure of liquidity for stocks with substantial commission-free retail activities, because commission-free retail orders flows are sold to wholesale market makers who are required by SEC to give order price improvement relative to the outstanding quotes on the public limit order book.[9]

Panel B shows that both the measures of intraday volatility are lower after the shutdown. However, intraday return autocorrelation and variance ratio in Panel C increase through the shutdown, which indicates a less efficient market. All of these differences are statistically significant at the 1% level.

Overall, the univariate tests suggest that after the shutdown the stock market is significantly more liquid and less volatile on the one hand, but less informationally efficient on the other hand. This suggests that a positive effect of the API shutdown on liquidity and volatility, but a negative effect on informational efficiency.

Panel D of Table 1 conducts similar univariate tests for the control variables. Only stock trading turnover has a statistically significant change due to the API shutdown. However, this change is not economically significant as its magnitude is almost zero.

3. The Effects of API Shutdown on Market Quality

3.1. Baseline regression results

The univariate tests reported in Table 1 suggest that Robinhood shutting its API down has mixed effects on different dimensions of market quality. To formally analyze the effects in a multivariate setting, we estimate the following regression:

$$MarketQuality_{i,d} = \beta_0 + \beta_1 Post_d + \delta Controls_{i,d} + \gamma FE_i + \epsilon_{i,d}, \qquad (1)$$

[9] https://www.sec.gov/tm/faq-rule-606-regulation-nms.

where subscripts i and d denote the stock and day, respectively, $MarketQuality$ represents one of the ten market quality measures discussed in Section 2.2, $Post_d$ is the indicator for whether day d is after the shutdown date (August 13, 2020), $Controls$ is the vector of control variables, and FE is the vector of stock fixed effects. Following Boehmer, et al. (2020), we standardize all continuous variables to have zero mean and unit variance within each stock to make the variations comparable across stocks. Robust standard errors are clustered by stocks and days. The coefficient of interest is β_1, which captures the average effect of the API shutdown on market quality. Since, all continuous variables are standardized within each stock, β_1 is interpreted in terms of standard deviations.

Table 2 presents the ordinary least square (OLS) estimation results of Equation (1). Panels A, B, and C report the results for stock liquidity, intraday volatility, and informational efficiency, respectively. The results are consistent with the findings from the univariate tests reported in Table 1. The shutdown of API reduces trading costs and make the stocks more liquid. It also reduces these stocks' volatility in intraday returns. On the other hand, these stocks' informational efficiency falls down. Importantly, the control variables in the model do not subdue the effects of shutdown although the magnitudes of the effects are smaller after these controls are considered.

Insert Table 2 here

These effects are economically meaningful. On the upside, Panel A shows that the shutdown leads to a remarkable reduction in trading costs as the effective spread is reduced by 26% of its standard deviations, even after controlling for volatility in daily returns, market cap, turnover, and the inverse of stock price. Likewise, Panel B indicates that the volatility in intraday returns falls by roughly 28% of its standard deviations. On the downside, Panel C implies that the shutdown increases intraday return autocorrelation by about 11% of its standard deviations and intraday return variance ratio by 17% of its standard deviations. These results suggest that the shutdown makes short-term stock returns more predictable and stock prices deviate more from the random walk process.

The termination of public access to Robinhood users' holding data yields improvement in stock liquidity that is similar to the effect of the removal of trader identities documented by Comerton-Forde & Tang (2009) and Meling (2021). Nevertheless, these two events differ in a couple of ways. First, Robinhood data provides information on trading activities of Robinhood investors which are only a subset of market participants, while trader identities provide information on activities of all market participants. Investors using commission-free trading platforms such as Robinhood differ substantially from other retail investors in their sophistication and trading behavior (Barber et al., 2021; Eaton et al., 2021; Welch, 2021). Second, information on Robinhood holdings is noisier as it contains only the number Robinhood users holding a particular stock (Welch, 2021). Thus, it requires a complex infrastructure and competent skills to extract valuable information for trading decision by processing Robinhood data. Individual investors are unlikely able to use this kind of data in their trading.

3.2. Heterogeneity of the effects of the API shutdown across stocks

If the effects of the shutdown of API on market quality are driven by the fact that some market participants are unable to access to the data of Robinhood users' holdings in individual stocks after the shutdown, we expect the effects to be stronger among stocks for which the Robinhood data is relatively more useful. We postulate that Robinhood data is more useful for stocks with greater Robinhood activities. As such, we define Robinhood (RH) stocks as stocks in the top quintile of Robinhood activities, which is measured as daily absolute Robinhood user change in the last five days preceding the API shutdown.

Table 3 compares the characteristics of RH stocks with those of non-RH stocks in the five trading days prior to the Robinhood API shutdown. The average trading volume for RH stocks is $5.09 million per day, while that for non-RH stocks is only $0.59 million. Turnover of RH stocks is also multiple times higher than those of non-RH stocks. In addition, RH stocks are substantially larger and more volatile than non-RH stocks. These differences are consistent with prior evidence on Robinhood investors' preference for high-volume, large-cap, and volatile stocks (e.g., Welch, 2021). There is no substantial difference in book-to-market ratio, book leverage, and market leverage between RH and non-RH stocks.

Insert Table 3 here

Figure 1 visualizes the variations of the market quality measure around the API shutdown separately for RH and non-RH stocks. Both RH and non-RH stocks experience decrease in spread and volatility but an increase in intraday return autocorrelation. Nevertheless, the changes appear to be more pronounced for RH stocks. Figure 1 also demonstrates parallel movements in market quality for RH and non-RH stock prior to the shutdown, which is an important condition for a difference-in-difference analysis

Insert Figure 1 here

To formally examine the difference in the effect of the API shutdown on RH versus non-RH stocks, we estimate the following model:

$$MarketQuality_{i,d} = \beta_0 + \beta_1 RH_i \times Post_d + \beta_2 RH_i + \beta_3 Post_d + \delta Controls_{i,d} + \epsilon_{i,d}, \quad (2)$$

where RH_i is the indicator for whether stock i is a Robinhood stock, and other variables are the same as the ones in Equation (1). The coefficient of interest is β_1, which captures the difference in the effects of the shutdown on market quality between RH and non-RH stocks. To economize the size of the paper, Table 4 only tabulates the results of one dependant variable for each of stock liquidity, intraday volatility and informational efficiency, and other results are available upon request.

Insert Table 4 here

As can be seen in Table 4, β_1 is statistically significant for all market quality measures. More importantly, the signs of the coefficient in all specifications are consistent with Figure 1. The magnitude of β_1 is around 0.2, which are substantial considering the average effects documented in Table 2. The results suggest that the shutdown has substantially larger effects on RH stocks than non-RH stocks, which is consistent with our conjecture that the effects are driven by the use Robinhood holdings data.

Our findings partly explain the increased stock liquidity and decreased intraday volatility during Robinhood platform outages documented by Eaton et al. (2021). They attribute the higher market quality in outages to reduced Robinhood trading activities due to their inability to trade. They support this view by arguing that zero-commission investors such as Robinhood investors increase inventory holding risk for market makers through their highly correlated trading activities so that market quality should improve following exogenous negative shocks to trading activities of these investors, such as in episodes of platform outages. We extend their argument by contending that the outages not only prevent Robinhood investors from trading but also disable all market participants utilizing the information imbedded in Robinhood holdings data. Therefore, the effect of the outages on market quality might be partly explained by missing of the Robinhood data.

Findings from this section also attenuate the concerns that the average effect documented in the previous section might be driven by some confounding market-wide events that occurred around the Robinhood API shutdown.[10] If changes in market quality are driven by a confounding market-wide event, we should observe parallel changes across all stocks. In contrast, we find significantly larger effects for stocks with more Robinhood activities.

4. Why Are the Effects of the API Shutdown Seemingly Contradicting?

4.1. Institutional algorithmic trading

In the previous section, we show that the termination of public access to Robinhood users' holdings data generates positive effect on stock liquidity and intraday volatility but negative effect on informational efficiency. What may be the probable underlying mechanism for these seemingly contradicting effects? This section addresses this question by recognizing the role of algorithmic trading by institutional investors.

High-frequency data such as data on retail order flows are mainly used by algorithmic traders rather than human traders, because processing them requires unique skills and infrastructure (Easley et al., 2016). Two major groups of algorithmic traders that account for most of the total trading volume are high-frequency market makers and institutional investors. However, both of them use trading algorithms in different ways. While high-frequency market-making firms use algorithms to quickly revise quotes to maximize profits and minimize the risk of liquidity provision, large institutions use algorithms to minimize trading costs and optimize their execution (Beason & Wahal, 2020; Hagströmer & Nordén, 2013). The latter are usually informed and a strategy they often employ is splitting individual parent orders into multiple child orders to hide their trading intentions. These institutional investors are often the trading counterparties of high-frequency market makers who are commonly viewed as uninformed traders (Beason & Wahal, 2020; O'Hara et al., 2014).

[10] For example, President Biden's announcement of Senator Harris as his choice for vice president also occurred on August 13, 2020, see https://www.nytimes.com/2020/08/13/us/politics/biden-harris.html.

Commission-free brokers such as Robinhood do not charge commission fees from their clients. Instead, they make revenue from selling their clients' order flows to high-frequency market-making firms. Therefore, the shutdown of API providing Robinhood users' unique accounts to the public is unlikely to affect high frequency market making firms' information set. In contrast, the shutdown denies the institutional investors' access to the data, which is likely to affect their algorithmic trading and execution optimization. To test this mechanism, we adopt a two-staged least square (2SLS) approach to examine institutional algorithmic trading. The first-stage regression is specified as:

$$OddLot_{i,d} = \beta_0 + \beta_1 Post_d + \delta Controls_{i,d} + \epsilon_{i,d}, \tag{3}$$

where $Oddlot$ is odd lot ratio, a proxy for institutional algorithmic trading, and other variables are as defined in Equation (1). If the shutdown decreases institutional algorithmic trading, β_1 should be negative.

As discussed earlier, the API shutdown should mainly affect algorithmic trading activities of institutional investors rather than those of market makers. To extract the part of $OddLot$ that is affected by the event, we obtain its fitted value $\widehat{OddLot}$ from the first-stage regression and then estimate the effects of this $\widehat{OddLot}$ on market quality by the following second-stage regression:

$$MarketQuality_{i,d} = \gamma_0 + \gamma_1 \widehat{OddLot}_{i,d} + \theta Controls_{i,d} + \nu_{i,d}. \tag{4}$$

If $\widehat{OddLot}$ reflects the algorithmic trading activities of institutional investors rather than uninformed market makers, it should have a positive relationship with bid-ask spread (or negative effect on stock liquidity) as privately informed trading by institutions increases the market makers' concern of adverse selection and in turn widened the spread. On the other hand, it should be negatively related to informational inefficiency measure such as stock return autocorrelation since new information owned by institutions is reflected in market in a timelier manner.

Table 5 reports the estimation results of regressions (3) and (4). Column 1 reveals that the shutdown reduces odd-lot trading by 12.95% of its standard deviation and the reduction is statistically significant at the 1% level. This finding is consistent with our conjecture that institutions conduct fewer informed trading because such trading is more difficult when the data of Robinhood users' holdings is no longer available to them.

Insert Table 5 here

For the second-stage regression, as Columns 2 and 4 show, $\widehat{OddLot}$ is positively associated with the effective spread while its relationship with stock return autocorrelation is negative. Combining this finding with the result from the first-stage regression, we demonstrate that the shutdown of API mainly reduces algorithmic trading activities of large institutions, which reduces informational efficiency because less informed trading is executed after the shutdown. Nevertheless, it also leads to a reduction in overall level of adverse selection risk and the reduced adverse selection risk allows market makers to quote narrower spreads or improve post-shutdown stock liquidity.

Columns 3 of Table 5 shows that $\widehat{OddLot}$ is positively associated with intraday volatility. This result can be explained by back-running activities. Since back-runners often monitor order flows to infer informed institutional orders and make profits by trading in the same direction as these informed orders (Yang & Zhu, 2020), back-running might increase inventory-holding risk, which leads market makers to revise quotes more often and creates excess short-term (intraday) volatility. Noting that the first-stage regression confirms a reduction in $\widehat{OddLot}$ because of Robinhood shutting API down, it implies a drop in back-running activities. This drop in turn leads to decrease in intraday volatility after the shutdown as unveiled in the baseline analysis.

4.2. Inferring fundamental information in retail order flow

Trading activities of Robinhood investors might contain fundamental information which can be exploited by sophisticated traders. Welch (2021) shows that a portfolio constructed using only Robinhood holdings data does not underperform the standard benchmarks. He argues that Robinhood investors, as a whole, have the "wisdom of the crowd", i.e., they are, in aggregate, able to pick stocks that do not underperform in the long run. Thus, the closure of the public access to Robinhood data makes sophisticated investors unable to infer information in Robinhood order flows. This reduces adverse selection costs, which help helps explain the improvement in liquidity. The inability to use Robinhood data also delays the incorporation of fundamental information into stock prices, which helps explain the drop in informational efficiency following the shutdown.

We examine this channel by first verifying whether information contained in Robinhood holdings data help predicting market-adjusted returns at horizons of one, five, and ten days. To this end, we estimate the following model:

$$\begin{aligned} CAR_{i,[d,d+\tau]} &= \beta_0 + \beta_1 RHChange_{i,d} + \beta_2 AggRetailOIB_{i,d} + \beta_3 CAR_{i,[d-1,d]}, \\ &+\beta_4 CAR_{i,[d-5,d-1]} + \beta_5 ESpread_{i,d} + \delta Controls_{i,d} + \epsilon_{i,d+1}, \end{aligned} \tag{5}$$

where $CAR_{i,[d,d+\tau]}$ is the cumulative market-adjusted return of stock i from day d to day $d+\tau$, $RHChange_{i,t}$ is the percentage change in the number of Robinhood holdings, $AggRetailOIB_{i,t}$ is the aggregate retail order imbalance calculated using the Boehmer et al. (2021) algorithm, and other variables are defined in the same way as in Equation (1). We estimate the Equation (5) using the Fama & MacBeth (1973) method. Our inferences are based on Newey & West (1987) standard errors with five lags to account for autocorrelation. The sample period is from the January 2, 2020 to August 13, 2020 when the API was turned off.

Table 6 reports the estimation results for Equation (5). Change in Robinhood holdings is statistically significant in negatively predicting future returns over one, five, and ten days, even after controlling for aggregate retail order imbalance and other predictors. The negative relationship between Robinhood holdings change and future return is consistent with Barber et al. (2021). Moreover, aggregate retail order imbalance positively predicts future return, which is also consistent with prior literature (e.g., Boehmer et al., 2021). These findings indicate that Robinhood holdings data contains information incremental to the information contained in aggregate retail order flows and other well-known predictors. Our findings provide suggestive evidence that access to Robinhood holdings data is valuable for some market participants to form profitable trading strategies.

Insert Table 6 here

If the Robinhood holdings data is used by some sophisticated traders to extract fundamental information for their trading, the shutdown of the data should protect Robinhood investors from such back-running behaviour. Thus, their profits should improve following the shutdown. We test this channel by examining the profits of retail investors around the API shutdown. We use the aggregate profits of all retail investors in our analysis, because lack of data does not allow us to estimate the profits of just Robinhood investors.

We calculate aggregate dollar profits following Barber et al. (2009) who argue that dollar profits provide a better proxy for the actual profits or losses of retail investors than abnormal returns, as abnormal returns might be artificially high on days with low trading volume. As such, for each-stock day, retail dollar profit is calculated as retail net purchase multiplied by cumulative market-adjusted return. To examine the change in trading profits of retail investors around the Robinhood API shutdown, we estimate the following equation:

$$RetailProfit_{i,[d,d+\tau]} = \beta_0 + \beta_1 RH_i \times Post_d + \beta_2 RH_i + \beta_3 Post_d + \delta Controls_{i,d} + \epsilon_{i,d}, \quad (6)$$

where the dependent variable $RetailProfit$ is aggregate retail profit, and other variables are defined in Equation (2). β_3 captures the effect of the event on retail profit in non-RH stocks, and β_1 captures the incremental effect on retail profit in RH stocks. Table 7 reports the estimation results for Equation (7).

Insert Table 7 here

The coefficient β_3 is not statistically significant in any specifications, suggesting that the Robinhood API shutdown has no effect on the trading profits of retail investors in non-RH stocks. The coefficient β_1 is statistically significant only for market-adjusted return at the five-day horizon. In sum, Table 7 provides weak evidence for the improvement in retail trading profits following the Robinhood API shutdown.

There are two possible explanations for the weak evidence. First, the dependent variable is the aggregate profit of all retail investors of which Robinhood investors are just a subset, while the API shutdown might mainly benefit Robinhood investors rather than other groups of retail investors. Second, data on Robinhood holdings might be mainly used by institutional investors who are informed and use the data only to optimize their execution, as discussed in Section 4.1, rather than uninformed back-runners.

5. Robustness Checks

In this section, we conduct various robustness tests to examine whether our results are robust to the choices of time horizon in calculating market quality measure, Robinhood activity proxy and institutional algorithmic trading proxy. We also check if our findings are the outcome of random variation in market quality measures over the sample period.

5.1. Stock liquidity measures at different horizons

Conrad & Wahal (2020) demonstrate that the two components of effective spreads, realized spread and price impact,[11] can be sensitive to the horizon used to calculate them. They show that the standard five-minute horizon is obsolete in modern market, especially for stocks whose liquidity is provided by high-frequency market makers. They suggest researchers adopting a range of shorter horizons to better capture actual trading costs and profits to market makers. Following this suggestion, we replicate the baseline results using the stock liquidity measures calculated at one-second, five-second, and ten-second horizons. Table 8 reports the results, which are similar to those reported in Table 2, both in terms of magnitude and statistical significance. This indicates that our findings are robust to the variation in time horizon used in calculating stock liquidity measures.

Insert Table 8 here

5.2. Alternative proxy for Robinhood activities

Absolute change in the number of Robinhood users holding a stock may be a noisy proxy for actual Robinhood activities in the stock (Welch, 2021), which potentially lead to measurement error. In particular, the proxy does not consider the size of the Robinhood investors' holdings. Thus, whether a position is only one share, or a thousand shares does not affect the proxy. The proxy also fails to capture instances when an investor buys additional shares for their existing position or when they sell part of their existing position.

To address the concern that our results in Section 3.2 may be driven by potential measurement errors, we re-estimate Equation (2) by using Reddit mentions of a stock to replace absolute Robinhood user change as the proxy for Robinhood activities. The variable $Reddit$ is

[11] Note that effective spread is equal to the sum of realized spread and price impact.

defined as the indicator for whether a stock is in top quintile of Reddit mentions. The results reported in Table 9 are largely consistent with those reported in Table 5, where Robinhood activities are proxied by absolute user changes. The similar results are expected, as the two Robinhood activity proxies are highly correlated in the cross-section of stocks.

Insert Table 9 here

5.3. Alternative proxy for institutional algorithmic trading

One concern with the algorithmic trading proxy $OddLot$ is that it might capture not only algorithmic trading activities of institutional investors but also trading activities of other groups of investors such as retail investors (Da et al., 2021). Thus, to check the robustness of the results obtained from the 2SLS approach, we replicate the regression using ISO, the percentage of daily trading volume attributed to intermarket sweep orders, to proxy for institutional algorithmic trading. Table 10 reports the results, which are qualitatively similar to those reported in Table 4, confirming the robustness of our findings.

Insert Table 10 here*5.4. Pseudo-events*

To eliminate the concerns that our results are driven by random time-series variation in market quality measures, we estimate the effects of two pseudo-events using the exact same specification used in Table 2. Table 11 presents the pseudo-events occurring exactly ten trading days before and after the actual event. Neither of the pseudo-events reveals a significant effect on market quality, which suggests that the effects documented in Table 2 are unlikely to be results by chance.

Insert Table 11 here

6. Conclusions

This paper examines the effect of the public availability of retail order flow data on various dimensions of market quality. To identify the causal effects, we exploit the shutdown of the public access to the data of Robinhood users' holdings as an exogenous shock. The shutdown has mixed effects: it improves stock liquidity and reduces intraday volatility but diminishes the informational efficiency of the market. These effects are more pronounced for stocks with greater Robinhood activities, which is consistent with the idea that the effects are driven by the market utilizing Robinhood data. We also find evidence for an explanation to the seemingly contradiction effects on market quality, i.e., the driving force for these effects are likely to be the algorithmic trading activities of institutional investors who are the major users of the Robinhood data prior to the shutdown.

Our paper contributes to the literature on transparency in financial markets and the growing literature on commission-free retail investors. Findings of this paper provide guidance to regulators on whether some types of information should be made publicly available. Specifically, it contributes to the debate on whether to allow retail brokers to disclose information on their clients' holdings.

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Figure 1: Market quality around the shutdown of API: RH vs non-RH stocks

This figure presents the variation in stock liquidity (ESpread), intraday volatility (SD10), and informational inefficiency (Autocorr10) around Robinhood shutting its users' holdings data down on August 13, 2020, separately for Robinhood (RH) stocks and non-RH stocks. A stock is defined as an RH stock if it is in the top quintile of Robinhood activities in the last five trading days prior to the shutdown.

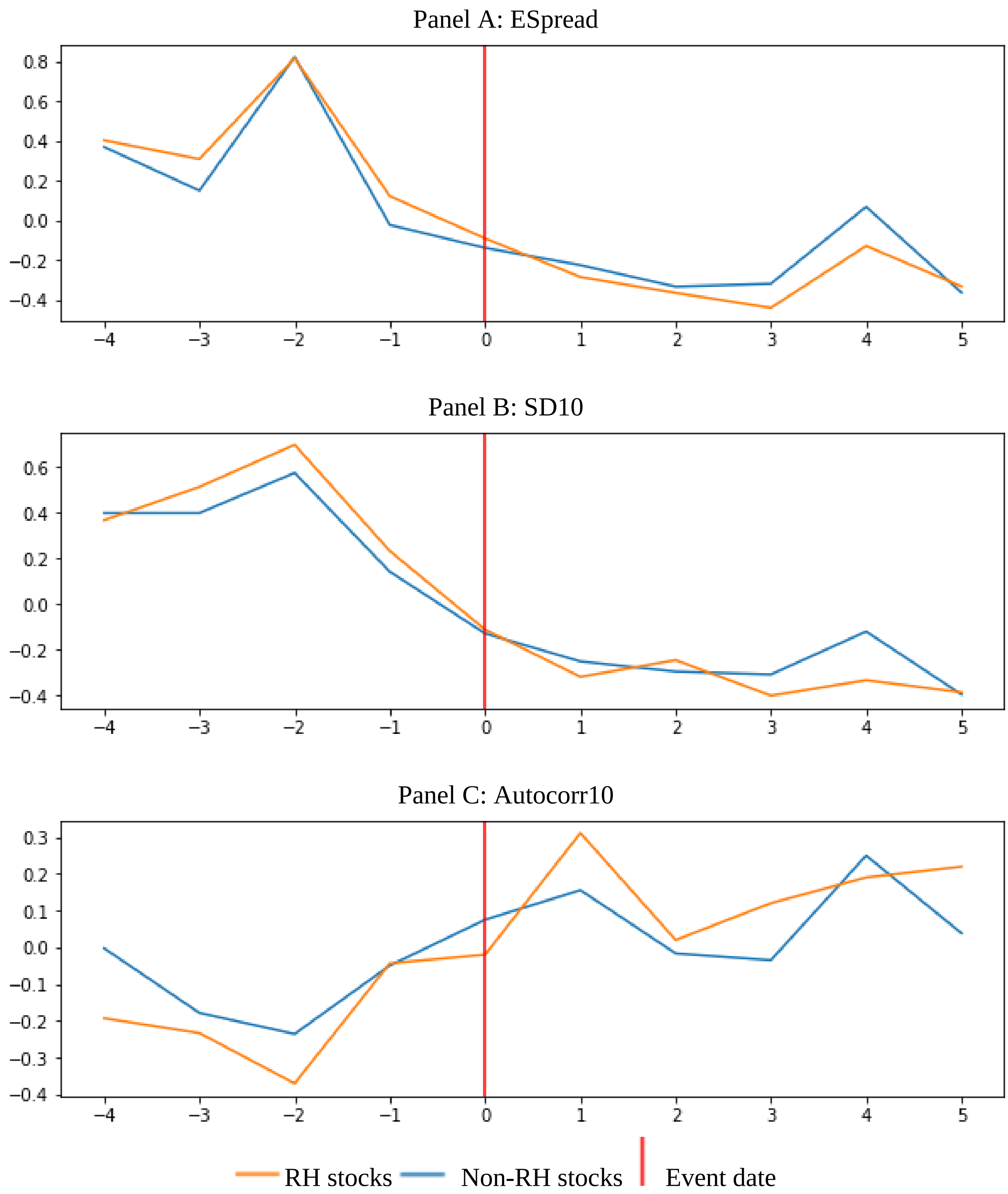

Table 1: Univariate tests of key variables

This table presents nonparametric tests for the key variables used in this paper. Columns 1 to 3 reports means, medians and standard deviations for the period five trading days prior to and including August 13, 2020. Columns 4 to 6 reports the number for five trading days after August 13, 2020. Columns 7 and 8 report the difference in means between post- and pre-events and its t-statistic. Symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Pre-shutdown			Post-shutdown			Difference	t-statistics
	Mean	Median	SD	Mean	Median	SD		
Panel A: Stock liquidity								
$ESpread$ (bps)	64.06	41.33	64.15	56.8	33.82	60.72	-7.26	(-10.08***)
$QSpread$ (bps)	59.1	26.46	88.23	57.04	24.46	85.92	-2.06	(-2.05**)
$RSpread$ (bps)	39.42	21.4	51.57	35.45	17.62	48.98	-3.97	(-6.85***)
$PriceImpact$ (bps)	24.43	16.01	31.16	21.46	12.86	30.41	-2.97	(-8.36***)
$Depth$ (‘000 shares)	24.35	14.03	30.38	24.89	14.19	32.1	0.54	(1.49*)
Panel B: Intraday volatility								
$SD10$ (bps)	15.47	12.47	10.77	12.99	10.26	9.56	-2.48	(-21.15***)
$SD60$ (bps)	22.86	18.56	15.96	18.28	14.3	13.64	-4.58	(-26.75***)
Panel C: Information efficiency								
$Autocorr10$	34.26	36.6	12.68	36.04	38.46	12.12	1.77	(12.4***)
$Autocorr60$	18.93	16.56	13.94	21.29	19.6	14.36	2.36	(14.49***)
VR	58.44	63.28	20.2	62.73	67	18.39	4.29	(19.27***)
Panel D: Control variables								
$DVolitility$	4.37	2.99	8.32	4.29	2.84	8.34	-0.07	(-0.78)
$LogMktCap$	6.89	6.85	2.11	6.89	6.84	2.12	0.00	(-0.18)
$Turnover$	0.01	0.01	0.03	0.01	0.01	0.02	0.00	(-9.56***)
$InvPrice$	0.11	0.05	0.16	0.11	0.05	0.16	0.00	-0.66

Table 2: The impact of API shutdown on market quality

This table presents the OLS estimation for the regressions of market quality on $Post_d$, which is the indicator for whether day d is after August 13, 2020. The explanatory variables include volatility in daily returns ($DVolatility$), the natural logarithm of market capitalization ($LogMktCap$), turnover ($Turnover$), and the inverse of stock price ($InvPrice$). Panels A, B and C document the results for stock liquidity, intraday volatility, and informational efficiency, respectively. Robust standard errors are double-clustered by stock and day are reported in the parentheses. Symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Stock liquidity

	$ESpread$	$QSpread$	$RSpread$	$PriceImpact$	$Depth$	$ESpread$	$QSpread$	$RSpread$	$PriceImpact$	$Depth$
$Post$	-0.5002***	-0.2630***	-0.3097***	-0.3213***	0.0773***	-0.2557**	-0.3602***	-0.1620***	-0.1629**	0.2271***
	(0.0111)	(0.0114)	(0.0114)	(0.0114)	(0.0115)	(0.1068)	(0.075)	(0.0613)	(0.071)	(0.0609)
$DVolatility$						0.0502**	0.005	0.0241*	0.0345**	0.0047
						(0.0206)	(0.0133)	(0.0123)	(0.0153)	(0.0113)
$LogMktCap$						0.0453*	-0.0033	0.0256	-0.0104	0.1057***
						(0.0261)	(0.0405)	(0.0372)	(0.0271)	(0.0375)
$Turnover$						0.4296***	-0.1457***	0.2685***	0.2726***	0.2517***
						(0.0238)	(0.0161)	(0.016)	(0.0205)	(0.0121)
$InvPrice$						0.0545*	0.1256***	0.0402	-0.0126	0.0076
						(0.0309)	(0.0354)	(0.0345)	(0.0288)	(0.043)
Observations	30,110	30,110	30,110	30,110	30,110	30,110	30,110	30,110	30,110	30,110
R-squared	0.0695	0.0192	0.0266	0.0287	0.0017	0.2481	0.0587	0.0952	0.1014	0.0748
Fixed Effects	Stock	Stock	Stock	Stock	Stock	Stock	Stock	Stock	Stock	Stock

Panel B: Intraday volatility

	SD10	SD60	SD10	SD60
$Post$	-0.5732***	-0.5922***	-0.2764***	-0.2838***
	(0.0110)	(0.0110)	(0.0520)	(0.0530)
$DVolatility$			0.0786***	0.0944***
			(0.0133)	(0.0213)
$LogMktCap$			0.0829***	0.0746**
			(0.0213)	(0.0302)
$Turnover$			0.5003***	0.5059***
			(0.0142)	(0.0175)
$InvPrice$			0.0563**	0.0411
			(0.0258)	(0.0266)
Observations	30,110	30,110	30,110	30,110
R-squared	0.0913	0.0974	0.3441	0.3618
Fixed Effects	Stock	Stock	Stock	Stock

Panel C: Informational efficiency

	Autocorr10	Autocorr60	VR	Autocorr10	Autocorr60	VR
$Post$	0.1939***	0.1937***	0.2904***	0.1131**	0.1032**	0.1660***
	(0.0115)	(0.0115)	(0.0114)	(0.0549)	(0.0427)	(0.0628)
$DVolatility$				-0.0508***	-0.0523***	-0.0621**
				(0.0191)	(0.0098)	(0.0257)
$LogMktCap$				-0.0171	0.0275	-0.0221
				(0.0485)	(0.0392)	(0.0493)
$Turnover$				-0.1084***	-0.1228***	- 0.1842***
				(0.0181)	(0.0131)	(0.0210)
$InvPrice$				-0.0070	0.0432	-0.0148
				(0.0504)	(0.0288)	(0.0384)
Observations	30,110	30,110	30,110	30,110	30,110	30,110
R-squared	0.0104	0.0104	0.0234	0.0257	0.0297	0.0622
Fixed Effects	Stock	Stock	Stock	Stock	Stock	Stock

Table 3: Characteristics of Robinhood stocks vs. non-Robinhood stocks

This table compares the characteristics of Robinhood stocks versus those of non-Robinhood stocks. A stock is classified as a Robinhood stocks if it is in the top quintile by Robinhood activities in the last five trading days prior to the API shutdown. Other stocks are classified as non-Robinhood stocks. The characteristics variables are calculated for five trading days prior to the Robinhood API shutdown on 13 August 2020.

	RH stocks			Non-RH stocks		
	Mean	Median	SD	Mean	Median	SD
Volume ($m)	5.09	1.87	10.89	0.59	0.24	1.33
Price ($)	66.32	16.00	188.95	49.04	21.47	124.41
Market cap ($m)	33,956	1,497	136,221	4,640	844	12,272
Book-to-market	0.03	0.02	0.03	0.03	0.02	0.04
Turnover	0.03	0.02	0.04	0.01	0.00	0.01
Volatility in daily returns (%)	6.06	4.22	9.58	3.90	2.76	7.93
Book leverage	6.07	2.24	34.48	4.47	2.23	10.12
Market leverage	0.13	0.04	0.44	0.13	0.05	0.38

Table 4: Robinhood activities and the effects of the API shutdown on market quality

This table presents the OLS estimation results of the following regression:

$$MarketQuality_{i,d} = \beta_0 + \beta_1 RH_i \times Post_d + \beta_2 RH_i + \beta_3 Post_d + \delta Controls_{i,d} + \epsilon_{i,d},$$

where i, d denote the stock and day, respectively, $MarketQuality$ is measured by either effective spread ($ESpread$) or intraday volatility ($SD10$) or stock return autocorrelation ($Autocorr10$), RH_i is the indicator for whether stock i is in the top quintile of Robinhood activities in the last five trading days prior to the shutdown, $Post_d$ is the indicator for whether day d is after August 13, 2020 when Robinhood shut its API down, and $Controls$ includes volatility in daily returns ($DVolatility$), the natural logarithm of market capitalization ($LogMktCap$), turnover ($Turnover$), and the inverse of stock price ($InvPrice$). Robust standard errors are double-clustered by stock and day and t-statistics are in the parentheses. Symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	$ESpread$	$SD10$	$Autocorr10$
$RH \times Post$	-0.2074***	-0.1922***	0.2180***
	(0.0733)	(0.0684)	(0.0562)
RH	0.1599**	0.1586***	-0.1270***
	(0.0640)	(0.0523)	(0.0371)
$Post$	-0.1123	-0.1249***	0.0361
	(0.0693)	(0.0375)	(0.0468)
$DVolatility$	0.0631***	0.0911***	-0.0561***
	(0.0237)	(0.0112)	(0.0198)
$LogMktCap$	0.0527**	0.0323*	0.0194
	(0.0211)	(0.0182)	(0.0250)
$Turnover$	0.4395***	0.5094***	-0.1091***
	(0.0332)	(0.0176)	(0.0179)
$InvPrice$	0.0573**	0.0022	0.0308
	(0.0289)	(0.0201)	(0.0314)
Observations	30,110	30,110	30,110
R-squared	0.2426	0.3343	0.0263
Fixed Effects	No	No	No

Table 5: The impact of institutional algorithmic trading

This table presents the 2SLS estimation for the impact of institutional algorithmic trading on market quality:

$$OddLot_{i,d} = \beta_0 + \beta_1 Post_d + \delta Controls_{i,d} + \epsilon_{i,d},$$
$$MarketQuality_{i,d} = \gamma_0 + \gamma_1 \widehat{OddLot}_{i,d} + \theta Controls_{i,d} + \nu_{i,d},$$

where $OddLot$ is the percentage of trading volume attributed to odd lot trades, $Post_d$ is the indicator for whether day d is after August 13, 2020, $\widehat{OddLot}$ is the fitted value of $OddLot$ from the first-stage, $MarketQuality$ is measured by either effective spread ($ESpread$) or intraday volatility ($SD10$) or stock return autocorrelation ($Autocorr10$), and $Controls$ includes volatility in daily returns ($DVolatility$), the natural logarithm of market capitalization ($LogMktCap$), turnover ($Turnover$), and the inverse of stock price ($InvPrice$). Robust standard errors are double-clustered by stock and day and t-statistics (?) are in the parentheses. Symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	First-stage	Second-stage		
	$OddLot$	$ESpread$	$SD10$	$Autocorr10$
$Post$	-0.1295***			
	(0.0096)			
$\widehat{OddLot}$		1.9648***	2.1259***	-0.8676***
		(0.1664)	(0.1682)	(0.1091)
$DVolatility$	0.0228***	0.0050	0.0305**	-0.0311***
	(0.0051)	(0.0127)	(0.0128)	(0.0082)
$LogMktCap$	-0.0354	0.1044	0.1581**	-0.0474
	(0.0274)	(0.0637)	(0.0629)	(0.0364)
$Turnover$	-0.5807***	1.5723***	1.7349***	-0.6123***
	(0.0049)	(0.0947)	(0.0959)	(0.0620)
$InvPrice$	-0.0533*	0.1486**	0.1696***	-0.0529
	(0.0274)	(0.0642)	(0.0634)	(0.0368)
Observations	30,110	30,110	30,110	30,110
Fixed Effects	No	No	No	No

Table 6: Robinhood ownership change and future returns

This table reports the daily Fama-Macbeth regression results of future market-adjusted returns $CAR_{i,[d,d+\tau]}$ on Robinhood percentage ownership change, $RHChange_{i,d}$, and a set of predictors including aggregate retail order imbalance ($AggRetailOIB_{i,d}$), lagged returns ($CAR_{i,[d-1,d]}$and $CAR_{i,[d-5,d-1]}$), lagged effective spread ($ESpread_{i,d}$), volatility in daily returns ($Dvolatility_{i,d}$), the natural logarithm of market capitalization ($LogMarketCap_{i,d}$), turnover ($Turnover_{i,d}$), and the inverse of stock price ($InvPrice_{i,d}$). Newey-West standard errors with five lags are reported in parentheses. Symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is 2 January 2020 to August 13, 2020.

	$CAR_{i,[d,d+1]}$	$CAR_{i,[d,d+5]}$	$CAR_{i,[d,d+10]}$
$RHChange_{i,d}$	-0.0209***	-0.0435***	-0.0659***
	(0.0057)	(0.0133)	(0.0132)
$AggRetailOIB_{i,d}$	0.0018***	0.0024**	0.0047***
	(0.0004)	(0.0010)	(0.0012)
$CAR_{i,[d-1,d]}$	-0.0304***	-0.0707***	-0.0584
	(0.0096)	(0.0268)	(0.0414)
$CAR_{i,[d-5,d-1]}$	-0.0152**	-0.0369*	-0.0160
	(0.0060)	(0.0222)	(0.0280)
$ESpread_{i,d}$	0.0102	-0.0017	-0.0302
	(0.0335)	(0.1292)	(0.2046)
$Dvolatility_{i,d}$	3.341e-05	0.0001	0.0003
	(9.576e-05)	(0.0004)	(0.0008)
$LogMarketCap_{i,d}$	-4.437e-05	-0.0002*	-0.0004***
	(5.501e-05)	(0.0001)	(0.0001)
$Turnover_{i,d}$	0.0051***	0.0200***	0.0355***
	(0.0012)	(0.0045)	(0.0069)
$InvPrice_{i,d}$	-0.4064***	-1.5269**	-2.8429**
	(0.1562)	(0.7477)	(1.4150)
Observations	424,698	424,698	424,698

Table 7: Aggregate retail trading profits around Robinhood API Shutdown

This table presents the OLS estimation results of the following regression:
$RetailProfit_{i,[d,d+\tau]} = \beta_0 + \beta_1 RH_i \times Post_d + \beta_2 RH_i + \beta_3 Post_d + \delta Controls_{i,d} + \epsilon_{i,d}$,
where i, d denote the stock and day, respectively, $RetailProfit_{i,[d,d+\tau]}$ is aggregate dollar profit of retail investors at τ-day horizon calculated following Barber et al. (2009), RH_i is the indicator for whether stock i is in the top quintile of Robinhood activities in the last five trading days prior to the shutdown, $Post_d$ is the indicator for whether day d is after August 13, 2020 when Robinhood shut its API down, and $Controls$ includes volatility in daily returns ($DVolatility$), the natural logarithm of market capitalization ($LogMktCap$), turnover ($Turnover$), and the inverse of stock price ($InvPrice$). Robust standard errors are double-clustered by stock and day and t-statistics are in the parentheses. Symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	$RetailProfit_{i,[d,d+1]}$	$RetailProfit_{i,[d,d+5]}$	$RetailProfit_{i,[d,d+10]}$
$RH_i \times Post_d$	0.0045	0.0466**	0.0126
	(0.0301)	(0.0221)	(0.0278)
RH_i	-0.0049	-0.0250*	-0.0005
	(0.0259)	(0.0150)	(0.0241)
$Post_d$	0.0052	0.0034	-0.0117
	(0.0083)	(0.0097)	(0.0079)
$DVolatility_{i,d}$	-0.0153***	0.0011	-0.0029
	(0.0041)	(0.0051)	(0.0053)
$LogMktCap_{i,d}$	0.0465	0.0544**	0.0663**
	(0.0363)	(0.0227)	(0.0271)
$Turnover_{i,d}$	-0.0006	-0.0083	-0.0028
	(0.0044)	(0.0071)	(0.0068)
$InvPrice_{i,d}$	0.0125	0.0021	0.0257
	(0.0342)	(0.0264)	(0.0319)
Observations	30,110	30,110	30,110
R-squared	0.0014	0.0029	0.0019
Fixed Effects	No	No	No

Table 8: Robustness checks: Alternative stock liquidity measures

This table corresponds to Panel A of Table 2 but stock liquidity measures are estimated at one-second, five-second or ten-second horizons. Variable $Post_d$ is the indicator for whether day d is after August 13, 2020 when Robinhood shut its API down, and control variables include volatility in daily returns ($DVolatility$), the natural logarithm of market capitalization ($LogMktCap$), turnover ($Turnover$), and the inverse of stock price ($InvPrice$). Columns 1 to 3 report the results for realized spreads estimated at 1-secion, 5-second and 10-second frequencies, respectively, while Columns 4 to 6 report the results for price impacts at these frequencies. Robust standard errors are double-clustered by stock and day and reported in parentheses. Symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	$RSpread1$	$RSpread5$	$RSpread10$	$PriceImpact1$	$PriceImpact5$	$PriceImpact10$
$Post$	-0.2144***	-0.1807***	-0.1846***	-0.1819*	-0.1751**	-0.1737*
	(0.0659)	(0.0632)	(0.0609)	(0.1068)	(0.0885)	(0.0887)
$DVolatility$	0.0303**	0.0260*	0.0322**	0.0423**	0.0402**	0.0333*
	(0.0139)	(0.0148)	(0.0163)	(0.0188)	(0.0190)	(0.0177)
$LogMktCap$	0.0097	0.0337	0.0066	0.0193	0.0241	0.0241
	(0.0389)	(0.0419)	(0.0481)	(0.0429)	(0.0301)	(0.0312)
$Turnover$	0.3422***	0.2876***	0.2693***	0.3500***	0.3233***	0.3216***
	(0.0183)	(0.0150)	(0.0171)	(0.0233)	(0.0226)	(0.0208)
$InvPrice$	0.0139	0.0421	0.0194	0.0317	0.0303	0.0283
	(0.0398)	(0.0419)	(0.0475)	(0.0493)	(0.0370)	(0.0367)
Observations	30,110	30,110	30,110	30,110	30,110	30,110
R-squared	0.1573	0.1109	0.1014	0.1587	0.1375	0.1344
Fixed Effects	Stock	Stock	Stock	Stock	Stock	Stock

Table 9: Robustness check: Alternative proxy for Robinhood activities

This table corresponds to Table 4 but Robinhood activities are proxied by $Reddit_i$, the indicator for whether stock i is in the top quintile of Reddit mentions in the last five trading days prior to the shutdown of Robinhood's API. In the table, dependent variable $MarketQuality$ is either effective spread ($ESpread$) or intraday volatility ($SD10$) or stock return autocorrelation ($Autocorr10$), variable $Post_d$ is the indicator for whether day d is after August 13, 2020 when Robinhood shut its API down, and control variables include volatility in daily returns ($DVolatility$), the natural logarithm of market capitalization ($LogMktCap$), turnover ($Turnover$), and the inverse of stock price ($InvPrice$). Robust standard errors are double-clustered by stock and day and reported in the parentheses. Symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	$ESpread$	$SD10$	$Autocorr10$
$Reddit \times Post$	-0.2652***	-0.2055***	0.2647***
	(0.0201)	(0.0190)	(0.0242)
Reddit	0.1853***	0.1644***	-0.1472***
	(0.0141)	(0.0134)	(0.0162)
$Post$	-0.1054***	-0.1232***	0.0298***
	(0.0078)	(0.0073)	(0.0089)
$DVolatility$	0.0609***	0.0893***	-0.0539***
	(0.0053)	(0.0050)	(0.0059)
$LogMktCap$	0.0545***	0.0322*	0.0181
	(0.0211)	(0.0181)	(0.0236)
$Turnover$	0.4384***	0.5091***	-0.1083***
	(0.0062)	(0.0057)	(0.0064)
$InvPrice$	0.0575***	0.0010	0.0312
	(0.0211)	(0.0181)	(0.0236)
Observations	30,110	30,110	30,110
R-squared	0.2442	0.3348	0.0276
Fixed Effects	No	No	No

Table 10: Robustness check: Alternative proxy for institutional algorithmic trading

This table corresponds to Table 5 and the first- and second-stage regressions are specified as the following:

$$ISO_{i,d} = \beta_0 + \beta_1 Post_d + \delta Controls_{i,d} + \epsilon_{i,d},$$
$$MarketQuality_{i,d} = \gamma_0 + \gamma_1 \widehat{ISO_{i,d}} + \theta Controls_{i,d} + \nu_{i,d},$$

where ISO is the percentage of trading volume attributed to intermarket sweep orders, $Post_d$ is the indicator for whether day d is after August 13, 2020, $\widehat{ISO}$ is the fitted value of ISO from the first-stage, $MarketQuality$ is either effective spread ($ESpread$) or intraday volatility ($SD10$) or stock return autocorrelation ($Autocorr10$), and $Controls$ includes volatility in daily returns ($DVolatility$), the natural logarithm of market capitalization ($LogMktCap$), turnover ($Turnover$), and the inverse of stock price ($InvPrice$). Robust standard errors are double-clustered by stock and day and reported in the parentheses. Symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	First-stage	Second-stage		
	ISO	$ESpread$	$SD10$	$Autocorr10$
$Post$	-0.2437***			
	(0.0116)			
ISO		1.0442***	1.1298***	-0.4611***
		(0.0661)	(0.0649)	(0.0515)
$DVolatility$	0.0526***	-0.0050	0.0196**	-0.0267***
	(0.0060)	(0.0098)	(0.0096)	(0.0076)
$LogMktCap$	0.0126	0.0216	0.0686*	-0.0109
	(0.0307)	(0.0431)	(0.0410)	(0.0333)
$Turnover$	-0.0667***	0.5009***	0.5757***	-0.1392***
	(0.0064)	(0.0092)	(0.0091)	(0.0071)
$InvPrice$	0.0046	0.0391	0.0511	-0.0045
	(0.0308)	(0.0432)	(0.0410)	(0.0333)
Observations	30,110	30,110	30,110	30,110
Fixed Effects	No	No	No	No

Table 11: Robustness checks: Pseudo-events

This table corresponds to Table 2 but considers pseudo shutdowns of Robinhood's API. Pseudo-events 1 and 2, respectively, occur ten trading days before and after the actual event. Market quality is measured by either effective spread ($ESpread$) or intraday volatility ($SD10$) or stock return autocorrelation ($Autocorr10$). Variable $Post_d$ is the indicator for whether day d is after the pseudo shutdown, and the control variables include volatility in daily returns ($DVolatility$), the natural logarithm of market capitalization ($LogMktCap$), turnover ($Turnover$), and the inverse of stock price ($InvPrice$). . Robust standard errors are double-clustered by stock and day and reported in parentheses. Symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Pseudo-event 1			Pseudo-event 2		
	$ESpread$	$SD10$	$Autocorr10$	$ESpread$	$SD10$	$Autocorr10$
$Post$	-0.0843	-0.0256	0.0177	0.0188	0.0641	-0.0828
	(0.0556)	(0.0606)	(0.0530)	(0.1369)	(0.1709)	(0.0727)
$DVolatility$	0.0304	0.1292***	-0.0795***	0.0476***	0.1118***	-0.0582***
	(0.0290)	(0.0284)	(0.0215)	(0.0127)	(0.0190)	(0.0154)
$LogMktCap$	-0.0360	-0.0016	0.0032	0.0677**	0.0746**	-0.0208
	(0.0361)	(0.0315)	(0.0330)	(0.0323)	(0.0376)	(0.0445)
$Turnover$	0.0217	0.5646***	-0.1008***	-0.0070	0.4439***	-0.0908***
	(0.0247)	(0.0127)	(0.0151)	(0.0179)	(0.0360)	(0.0192)
$InvPrice$	0.0243	-0.0191	-0.0094	0.1683***	0.1093	-0.0218
	(0.0374)	(0.0334)	(0.0340)	(0.0525)	(0.0740)	(0.0558)
Observations	30,110	30,110	30,110	30,110	30,110	30,110
R-squared	0.0060	0.3400	0.0137	0.0125	0.2212	0.0142
Fixed Effects	Stock	Stock	Stock	Stock	Stock	Stock