EXHIBIT 42

The Journal of FINANCE
The Journal of THE AMERICAN FINANCE ASSOCIATION

THE JOURNAL OF FINANCE • VOL. LXXVII, NO. 6 • DECEMBER 2022

Attention-Induced Trading and Returns: Evidence from Robinhood Users

BRAD M. BARBER, XING HUANG, TERRANCE ODEAN, and CHRISTOPHER SCHWARZ*

ABSTRACT

We study the influence of financial innovation by fintech brokerages on individual investors' trading and stock prices. Using data from Robinhood, we find that Robinhood investors engage in more attention-induced trading than other retail investors. For example, Robinhood outages disproportionately reduce trading in high-attention stocks. While this evidence is consistent with Robinhood attracting relatively inexperienced investors, we show that it is also driven in part by the app's unique features. Consistent with models of attention-induced trading, intense buying by Robinhood users forecasts negative returns. Average 20-day abnormal returns are −4.7% for the top stocks purchased each day.

OVER THE PAST HALF-CENTURY, INVESTOR trading has changed significantly. Decades ago, retail investors traded via phone only during market hours, paying heavy commissions to do so. The 1990s brought about online trading and significantly lower commissions. More recently, the fintech brokerage Robinhood brought about even more changes, as the first brokerage to offer commission-free trading on a convenient, simple, and engaging mobile app. How do these changes in the investment landscape affect individual investors' trading behavior?

*Brad M. Barber is at Graduate School of Management, UC Davis. Xing Huang is at Olin Business School, Washington University in St. Louis. Terrance Odean is at Haas School of Business, UC Berkeley. Christopher Schwarz is at Merage School of Business, UC Irvine. We appreciate the comments of Azi Ben-Rephael (discussant); Charles Jones (discussant); Michaela Pagel (discussant); Ivo Welch; and seminar and conference participants at the University of Central Florida, the University of Missouri, Erasmus University Rotterdam, Maastricht University, Ohio State University, Q Group, 3rd Virtual QES NLP and Machine Learning in Investment Management Conference, FSU SunTrust Beach Conference, the 2021 SFS Cavalcade, China Meeting of the Econometric Society, WFA 2021, and EFA 2021. We also thank Paul Rowady, Jr. at Alphacution. Finally, we appreciate the helpful comments and guidance of the editor, associate editor, and reviewers. None of the authors has conflicts of interest to disclose. Barber serves on the advisory board of Vert Asset Management. Odean is a member of the academic advisory board of Matson Money, an advisory editor to the *Financial Planning Review*, a member of the academic advisory board of *The Journal of Investment Consulting*, and was previously a member of the academic advisory board of Russell Investments.

Correspondence: Xing Huang, Washington University, Olin Business School, One Brookings Drive, St. Louis, MO 63130-4899; e-mail: xing.huang@wustl.edu. Christopher Schwarz, University of California Irvine, Merage School of Business, Irvine, CA 92697-3125; e-mail: cschwarz@uci.edu

DOI: 10.1111/jofi.13183

On the one hand, the lack of commissions and the simple trading interface may reduce the costs and barriers to investing in the stock market. Because even small costs can reduce stock market participation among less wealthy households (Vissing-Jorgensen (2002)), Robinhood and similar fintech applications may increase stock market participation and bring new investors into the stock market.

On the other hand, gamification and simplicity can influence trading behavior in ways that might redound to the detriment of investors. To its app, Robinhood "added features to make investing more like a game. New members were given a free share of stock, but only after they scratched off images that looked like a lottery ticket."[1] New and inexperienced investors may find these features appealing, but some believe that Robinhood overemphasizes the fun of trading at the cost of sound investment practices. For example, in December 2020, Massachusetts state regulators filed a complaint against Robinhood citing its "aggressive tactics to attract inexperienced investors" and "use of strategies such as gamification to encourage and entice continuous and repetitive use of its trading application."[2] Indeed, Robinhood users are unusually active; in the first quarter of 2020, 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 most recent quarter."[3] Thus, while Robinhood's innovations may have had a positive effect on market participation (and Robinhood's customer acquisition), their effect on trading behavior is an open question. With these issues in mind, in this paper we study the behavior of Robinhood users using data on aggregate Robinhood user changes at the stock-day level from May 2018 to August 2020.

We first conjecture that Robinhood users are more likely to be influenced by attention than other investors. Half of Robinhood users are first-time investors[4] who are unlikely to have developed their own clear criteria for buying a stock. Inexperienced stock investors are more heavily influenced by attention (Seasholes and Wu (2007)) and by biases that lead to return-chasing (Greenwood and Nagel (2009)). With turnover rates many times higher than those of other brokerage firms, Robinhood users are more likely to trade speculatively. As a result, a smaller proportion of their trading is motivated by nonspeculative objectives such as saving for retirement, meeting liquidity needs, harvesting tax losses, or rebalancing their portfolio. The higher rate of speculative trading by Robinhood users thus increases the potential for attention-driven trading.

If Robinhood users are more likely than other investors to be influenced by attention, their purchase behavior is more likely to be correlated, that is, they

[1] See https://www.nytimes.com/2020/07/08/technology/robinhood-risky-trading.html.

[2] See https://www.sec.state.ma.us/sct/current/sctrobinhood/MSD-Robinhood-Financial-LLC-Complaint-E-2020-0047.pdf.

[3] See https://www.nytimes.com/2020/07/08/technology/robinhood-risky-trading.html.

[4] See https://blog.robinhood.com/news/2020/5/4/robinhood-raises-280-million-in-series-f-funding-led-by-sequoia.

are more likely to herd than other investors.[5] This is exactly what we find. We document that 35% of net buying by Robinhood users is concentrated in 10 stocks compared to 24% of net buying by the general population of retail investors. We then analyze herding episodes by Robinhood users. We define a herding episode as a day when the number of Robinhood users owning a particular stock increases dramatically. In our primary analysis, we focus on the top 0.5% of positive user changes as a percent of prior-day user count each day. This represents about 10 herding episodes per day or almost 5,000 episodes over the 26-month sample period. We show that these herding episodes are predicted by attention measures (e.g., recent investor interest, extreme returns, or unusual volume). Finally, we show that during Robinhood outages, retail trading drops more in high-attention stocks than in other stocks relative to periods with no outage. The findings based on Robinhood outages provide strong evidence that Robinhood users are more likely to engage in attention-induced trading than other retail investors.

The simplicity of Robinhood's app is likely to guide investor attention. The app prominently displays lists of stocks in an environment relatively free of complex information. For example, besides basic market information, Robinhood provides only five charting indicators, while TD Ameritrade provides 489.[6] This streamlined and simplified interface likely guides the choices of Robinhood users. Moreover, the Robinhood app makes it very easy to trade on these guided choices. The basic information display and trading simplicity offered by the app reduces cognitive burdens, which leads investors to rely more on their intuition and less on critical thinking, or more on System 1 and less on System 2 thinking (Kahneman (2011)). Of course, the Robinhood app is not the only channel through which Robinhood users' attention becomes focused on a common subset of stocks; for example, many Robinhood users share information and opinions on online forums such as Reddit's WallStreetBets.[7]

To identify the effect of the app on Robinhood users, we focus on the "Top Movers" list, which comprises only 20 stocks and changes every day (and throughout each day). Crucially, this list displays stocks with the largest absolute percentage price changes from the previous-day close. In contrast, many websites provide separate lists of stocks with the largest daily gains and losses (e.g., Yahoo! Finance Gainers and Yahoo! Finance Losers), and on these sites top gainers tend to be more prominently displayed. Moreover, Google search volume suggests that investors are about twice as likely to look for stocks with

[5] We focus on purchase herding because retail investors tend to buy rather than sell attention-grabbing stocks because retail investors tend to sell what they own, hold few stocks, and engage in limited short selling (Barber and Odean (2008)). Consistent with this evidence, we find that sales herding events in the Robinhood data are less dramatic (see Section III.F). In contrast, institutions hold many stocks and engage in short selling. Thus, the institutional herding literature has not drawn a distinction between purchase and sales herding (e.g., Lakonishok, Shleifer, and Vishny (1992)).

[6] See https://www.stockbrokers.com/compare/robinhood-vs-tdameritrade.

[7] See https://www.wsj.com/articles/the-real-force-driving-the-gamestop-amc-blackberry-revolution-11611965586?page=1.

same-day gains than those with same day losses.[8] Thus, if the app itself is driving Robinhood users' trading, we would expect Robinhood traders to buy both gainers and losers heavily, while other retail investors will tend to buy gainers. This is precisely what we find: Robinhood users are drawn to trading both extreme gainers and extreme losers, whereas other retail investors prefer to buy extreme gainers. While prior work documents that investors buy extreme winners and losers (Barber and Odean (2008)), our evidence indicates the Robinhood app affects the intensity of this behavior because of the unique way Robinhood displays the Top Movers list.

We provide additional evidence that the Top Movers list influences Robinhood user buying behavior by exploiting another unique feature of the list. Robinhood requires stocks above $300 million in market capitalization to be displayed in the Top Movers list. We use a sharp regression discontinuity design to show that Robinhood users are more likely to buy stocks with market capitalization between $300 million and $350 million that were in the top 20 stocks when sorting on absolute returns than stocks with similar absolute returns but market capitalization between $250 million and $300 million. Thus, stocks that just miss making the list due to market capitalization below the $300 million cutoff do not observe the increase in users associated with being on the Top Movers list. This evidence indicates that the display of information affects investors' trading.

Models of attention-induced trading and returns predict that periods of intense buying will be followed by negative abnormal returns (e.g., Barber and Odean (2008), Pedersen (2022)). We conjecture that the concentrated buying of Robinhood users, who are susceptible to attention-induced trading, provides an unusually strong setting to identify the return effects of attention-induced trading. In our final set of analyses, we focus on this return prediction and document large negative abnormal returns following Robinhood herding episodes. Specifically, the top 0.5% of stocks bought every day lose about 4.7% over the subsequent month.

The magnitude of the negative abnormal returns increases dramatically as we identify fewer but more intense herding episodes. To systematically analyze the relation between the herding intensity and price reversal, we focus on stocks with a minimum of 100 Robinhood users and identify different sets of herding episodes by varying the daily percentage increase in users holding the stock from 10% to 750%. At a 10% increase in users, we observe over 20,000 herding episodes, while at a 750% increase, we observe 45 episodes. The large negative abnormal returns in the month following these herding events grow from a statistically significant −1.8% when we require a 10% increase in users (>20,000 events) to an extremely large and statistically significant −19.6% when we require a 750% increase in users (45 events).

[8] Google trends indicates that the phrase "top gainers today" ("top stock gainers today") is searched more than twice as much as "top losers today" ("top stock losers today") over the five years beginning January 24, 2016.

The negative returns that follow purchase herding by Robinhood users are not simply inventory-based reversals as modeled in Jagadeesh and Titman (1995) and documented around earnings announcements in So and Wang (2014). Attention-induced trading can also cause return reversals when investors tend to buy stocks with strong recent returns. However, the negative returns following herding episodes are not limited to return reversals. First, in multivariate analyses, in which we control for return reversals, the negative abnormal returns following herding episodes remain large and statistically significant. Second, and more importantly, we observe negative returns following a day when we observe a surge in Robinhood users that is preceded by an overnight drop in the stock's price, perhaps because aggressive Robinhood investor buying slows the stock's response to negative news (Barber and Odean (2008)). The negative returns that we document following purchase herding by Robinhood users are also not driven by the bid-ask spread since they persist when we use quote midpoints to calculate returns.

Given the relatively small size of Robinhood, one might question whether Robinhood users have the potential to influence market prices. Robinhood has $81 billion in assets under custody,[9] far less than E*TRADE at $600 billion, TD Ameritrade at $1.3 trillion, and Charles Schwab at $3.8 trillion.[10] However, trades, not passive positions, move prices. There are a lot of Robinhood users: 13 million as of May 2020 compared to 12.7 million at Schwab and 5.5 million at E*TRADE at the end of 2019.[11] Moreover, as noted above, Robinhood users are extremely active traders. In June 2020, Robinhood users averaged 4.3 million revenue trades per day (Daily Average Revenue Trades or DARTs), more than E*TRADE at 1.1 million, TD Ameritrade at 3.8 million, Charles Schwab at 1.8 million, Interactive Brokers at 1.9 million, or Fidelity at 1.4 million.[12] Thus, Robinhood users accounted for roughly 30% of daily trades from the largest brokerage firms catering to retail investors and have the potential to move prices. In Q1 2020, Robinhood's order routing revenue was 21.5% of that of Robinhood, TD Ameritrade, E*Trade, and Schwab combined, and its shares traded were 12.4%. Robinhood users also favored trading non-S&P 500 stocks more than did the clients at the three other firms.[13] Thus, by several measures, Robinhood accounted for a material fraction of retail trading, particularly for smaller-capitalization stocks. Furthermore, as noted above, Robinhood trades may be a good proxy for the actions of other attention-motivated traders who herd in the same stocks.

[9] See p. 26 of Robinhood's SEC Form S1 IPO filing (https://www.sec.gov/Archives/edgar/data/1783879/000162828021013318/robinhoods-1.htm).

[10] See https://www.businessofapps.com/data/robinhood-statistics/.

[11] See https://www.nytimes.com/2020/07/08/technology/robinhood-risky-trading.html.

[12] See https://www.bloomberg.com/news/articles/2020-08-10/robinhood-blows-past-rivals-in-record-year-for-retail-investing. Fidelity's daily trades are for all of 2020, not just June (https://www.barrons.com/articles/fidelitys-trading-volume-surged-in-the-pandemic-but-its-struggling-to-boost-revenue-51614702735). Note that brokerages exercise some discretion in measuring DARTs.

[13] Case Study: The Robinhood Effect, Alphacution, July 2021.

Two additional findings indicate that the negative returns we observe are due at least in part to the trading of Robinhood users and other attention-motivated retail investors. First, we expect the influence of investors to be most pronounced among small-cap stocks. In the cross section, we find negative returns following Robinhood herding events for stocks with market cap under $1 billion, but not for stocks with market cap over $1 billion. Second, we expect larger effects during periods with heightened retail trading. In the time series, retail trading increased significantly at Robinhood and elsewhere during the COVID-19 period (i.e., after March 13, 2020), and the negative return effect following Robinhood herding events is more pronounced in this period. Irrespective of whether the negative returns we document result from the trading of Robinhood users and other attention-motivated retail investors, these negative returns lead to trading losses for many investors.

Savvy investors might exploit the trading patterns and negative returns that we document. To profit from Robinhood herding events, an investor would need to sell the stock short (or, equivalently, purchase put options that the option seller would hedge by shorting). Thus, if investors are exploiting Robinhood user herding, we would expect to see increased short interest around Robinhood user herding events. We do indeed find a marked increase in short selling for stocks involved in Robinhood herding events even after controlling for returns and news.

While the Top Movers list and possibly other features of the Robinhood app influence Robinhood users, many drivers of attention will affect Robinhood users and other retail investors similarly. We show that this is the case using a measure of retail investor herding developed by Barber, Lin, and Odean (2021, BLO). BLO classify herding events as Trade and Quote (TAQ) retail trades in the top quintile of retail standardized order imbalance (*SOI*) and top decile of abnormal retail volume. For each day in our Robinhood sample, we modify the BLO methodology to identify the same number of TAQ herding events as we identify using our Robinhood herding measure. We find that 27% (1,317 of 4,884) of the Robinhood and BLO herding events are identical. Like Robinhood herding events, these events are, on average, followed by negative returns. However, the 21% (1,008 of 4,884) of the Robinhood herding events that are accompanied by retail selling on TAQ also earn negative returns, and the subsequent negative returns for non-Robinhood herding events are smaller in magnitude than those related to Robinhood events. These results show that the actions of Robinhood users are a good proxy for attention-induced trading.

Our study is of particular interest given the unique data set of the retail investors (Robinhood users) that we analyze. To our knowledge, four papers use the same. Welch (2022) analyzes the holdings and performance of Robinhood users. He concludes that Robinhood users principally held stocks with large persistent past volume and do not underperform with respect to standard academic benchmark models.[14] In a JP Morgan report, Cheng, Murphy,

[14] We too find that the aggregate performance of Robinhood users is not reliably different from zero using standard asset pricing technology. See Table IAI.

and Kolanovic (2020) show that users are drawn to stocks that attract investor attention and that changes in stock popularity predict returns. Unlike these studies, we document poor returns following extreme attention-driven herding events by Robinhood users. Ozik, Sadka, and Shen (2021) use the Robintrack data to analyze the sharp increase in retail trading and the effect on bid-ask spreads during the pandemic period. They find an increase in trading of stocks with COVID-19 media coverage, which they attribute to an attention-grabbing effect. They also document that the increase in retail trading generally lowered stock bid-ask spreads and that price impact of trades. Similarly, Eaton et al. (Forthcoming) use Robinhood outages to study the effect of retail trading on market quality and find that these negative shocks to Robinhood participation reduce market volatility and improve liquidity. In contrast to these studies, we study the attention-induced trading of Robinhood investors and show that herding episodes by Robinhood investors reliably predict negative returns.

In summary, we provide two main contributions to the academic literature. First, we present evidence that the Robinhood app influences investors' behavior. Specifically, we show that the prominently featured Top Movers list (which displays only 20 stocks, sorts stocks on absolute [rather than signed] percentage returns, and changes regularly) affects Robinhood users. This finding fits into the emerging literature that emphasizes that the display of information affects investor behavior. Changes in the display of price information affect investors' willingness to sell winners versus losers in individual stocks and mutual funds (Frydman and Wang (2020), Loos, Meyer, and Pagel (2020)). News that investors consume about stocks often confirms their prior beliefs (Cookson, Engelberg, and Mullins (Forthcoming)), and its prominence affects the incorporation of information (Fedyk (2019)). Displaying return performance for index funds can lead investors to prefer high-fee funds (Choi, Laibson, and Madrian (2010)), prominently featuring expense information can lead investors to prefer low-fee funds (Kronlund et al. (2021)), and the prominence of mutual fund lists affects investors' fund choices (Kaniel and Parham (2017), Hong, Lu, and Pan (2019)).[15] Our results, and this emerging literature, indicate that disclosure alone is not sufficient to assure good investor outcomes—how information is displayed can both help and hurt investors. Furthermore, while the recent literature on complexity in finance emphasizes its dark side (Carlin (2009)), our results suggest that simple user interfaces are not necessarily the solution to problems that arise from complexity—both complexity and simplicity can lead investors astray.

Second, we contribute to the literature that documents the effects of attention-induced trading on returns. Using Robinhood trading as a proxy for attention-induced herding episodes, we find strong support for the return predictions of attention-based models of trading. Specifically, we link episodes of

[15] Da et al. (2018) find that recommendations of an advisory firm followed by many Chilean pension investors generate correlated fund flows and influence market returns. These attention-induced effects on the active choice of mutual funds are different from the stickiness of default options (e.g., Cronqvist and Thaler (2004)), which might result from inertia or a view that defaults are an implicit recommendation.

intense buying by Robinhood users to negative returns following the herding episodes. Our focus on trading rather than events is distinct from extant literature that focuses on events such as Jim Kramer's stock recommendations (Keasler and McNeil (2010), Bolster, Trahan, and Venkateswaran (2012), Engelberg, Sasseville, and Williams (2012)), the WSJ Dartboard Column (Barber and Loeffler (1993), Liang (1999)), Google stock searches (Da, Engelberg, and Gao (2011), Da et al. (2020)), and repeat news stories (Tetlock (2011)). Perhaps as a result of our focus on trading behavior rather than events, the return reversals that we document are much larger and more widespread than those documented in prior studies.[16] Moreover, the extant literature documents negative returns subsequent to positive return events, while we find negative returns following intense buying that coincides with or follows negative returns.

The paper proceeds as follows. Section I provides a detailed description of our data set. Section II presents our empirical analysis of Robinhood investors' attention-induced trading and the role of the app's unique features. Section III shows the return effect of Robinhood users' attention-induced trading. Section IV discusses the short-trading activities associated with the intense buying by Robinhood users. Section V concludes.

I. Data and Methods

In this section, we describe the main Robintrack data set that keeps track of how many Robinhood users hold a particular stock over time and our methods for identifying extreme herding events by Robinhood users.

A. Robintrack Data

The primary data set for our analysis comes from the Robintrack website (https://robintrack.net/), which scrapes stock popularity data from Robinhood between May 2, 2018, and August 13, 2020.[17] Robinhood discontinued the reporting of stock popularity data on August 13, 2020. The Robintrack data set contains cross-sectional snapshots of user counts for individual securities (e.g., 645,535 Robinhood users held Apple stock at 3:46 pm ET on August 3, 2020).[18] Our main results include all Robintrack securities since we do

[16] See Table IAII for a summary of these studies. The biggest magnitude of return reversal is −4.6% for 39 events over three years (Barber and Loeffler (1993)). In a widely cited study, Da, Engelberg, and Gao (2011) fail to find robust evidence of price reversals following spikes in Google search volume.

[17] About 11 dates during the sample period are missing user data, four in January 2019 and seven in January 2020. For 16 dates on which we observe users, no observations were recorded between 2 and 4 pm ET.

[18] The Robintrack data are generally reported every hour at approximately 45 minutes after the hour. The data from Robinhood have some lag. For example, the user count on Robintrack for Apple at 3:46 pm is from sometime before 3:46 pm. Based on analysis of open data, the lag is likely between 30 and 45 minutes. The Robinhood app appears to update data every 15 minutes.

not have strong priors about what types of securities will experience herding events.[19]

We merge the Robintrack data to the Center of Research in Security Prices (CRSP) and TAQ data by using the ticker on Robintrack. The CRSP database provides daily returns, closing and opening prices, closing bid-ask spreads, and market capitalization. We use the TAQ database to identify retail buys and sells using the Boehmer et al. (2021) algorithm. This algorithm relies on the observation that retail trades often receive price improvement in fractions of a penny and are routed to a Financial Industry Regulatory Authority (FINRA) trade reporting facility (TRF). The algorithm therefore identifies retail buys as trades reported to a FINRA TRF (exchange code "D" in TAQ) with fractional penny prices between \$0.006 and \$0.01, and retail sells as trades reported to a FINRA TRF with fractional penny prices between \$0.00 and \$0.004.[20]

In Figure 1, Panel A, we see that the total number of Robinhood user-stock positions grew from about 5 million at the beginning of our sample period to more than 42 million at the end. In May 2020, Robinhood reported having 13 million users, which translates to about three stock positions per user.[21] The red vertical line in the figure denotes the date on which the COVID-19 national emergency was declared in the United States (March 13, 2020). A clear increase in Robinhood users can be seen after this date. In Figure 1, Panel B, we plot the total number of TAQ retail trades for comparison. We find that retail trading also increased during the pandemic period. Of course, some Robinhood trades are part of these retail trades.

The Robintrack data do not allow us to identify individual trades, but they do allow us to analyze changes in user positions in a particular stock. The analog to this Robinhood user change variable in TAQ is net retail buying in a stock. In Figure 1, Panel C, we plot the five-day moving average of the daily sum across stocks of the absolute value of Robinhood user changes (green line) and the five-day moving average of the daily sum across stocks of the absolute value of TAQ net buying, that is, the number of retail buys minus the number of retail sells (blue line). Both measures of trading activity follow similar trajectories, with a marked increase in the pandemic period.

We present additional summary statistics in Table I, Panel A, across stock-day observations. The main variable, *users_close*, measures the total number of users in a stock prior to the close of trading (4 pm ET) but after 2 pm on the same day. The key variables in our analysis of herding events are based on the daily changes in *users_close* (*userchg*) or the ratio of *users_close* on consecutive days (*userratio*). For descriptive purposes, we also report *users_last*, which is

[19] The results are similar for common stocks and other securities, though U.S. common stocks represent 70% of all herding episodes, stocks with non-U.S. headquarters 13%, and American Depositary Receipts (ADRs) 10%.

[20] We also use TAQ to calculate returns in July and August 2020 since CRSP data were not available through August 2020 at the writing of this draft.

[21] See "Robinhood Has Lured Young Traders, Sometimes with Devastating Results" in *The New York Times*, July 8, 2020 (https://www.nytimes.com/2020/07/08/technology/robinhood-risky-trading.html).

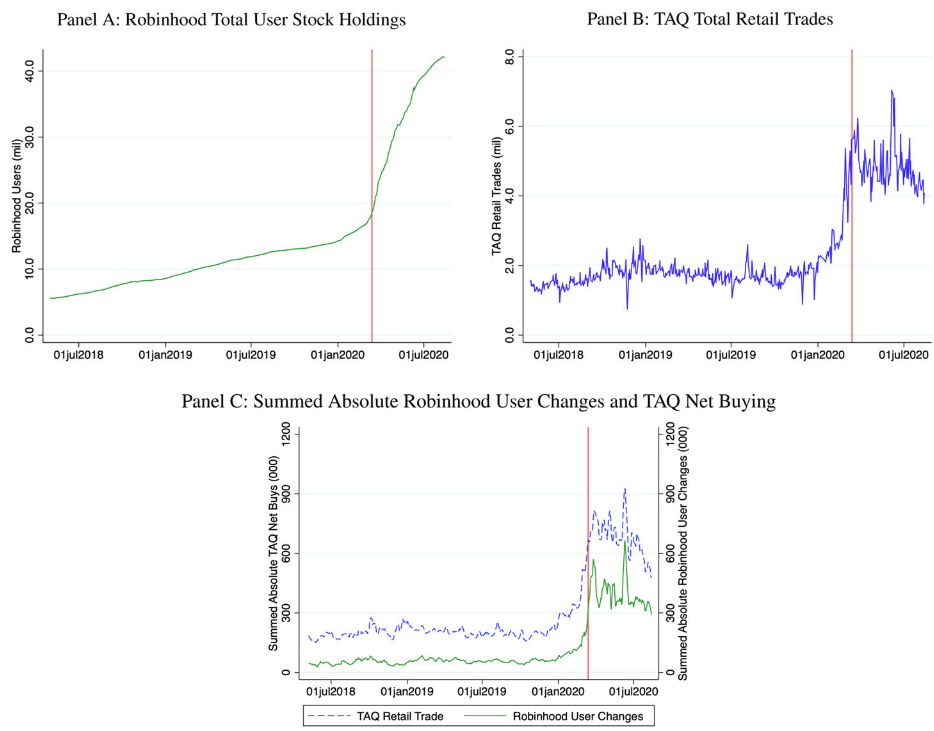

Figure 1. Robinhood and TAQ retail trading. Panel A plots the total number of Robinhood stock holdings. Panel B plots the total number of TAQ Retail Trades. Panel C plots the total number of absolute Robinhood user changes (green) and absolute TAQ net buys (blue) as a five-day moving average. The red vertical line depicts the date when the COVID national emergency was declared in the United States (March 13, 2020). (Color figure can be viewed at wileyonlinelibrary.com)

the last reported user count for a stock on each day, regardless of the time of reporting.

The mean stock has a bit more than 2,000 users, though the median user count is 160. User changes are generally small—the interquartile range of *userchg* is 2 and that of *userratio* is 0.01. Similarly, TAQ net buying is generally quite small, with an interquartile range of −7 to +10. In Table I, Panel B, we present descriptive statistics across days. The average day has 7,211 stock holdings and just under 15 million user positions.

B. Herding Events

While we find that user changes are generally small, a number of extreme user change events are in our sample. These extreme events likely occur because Robinhood users are new to markets and more willing to speculate. These extreme events are also likely a good proxy for the behavior of investors who are unduly influenced by attention-grabbing events. To

Table I

Summary Statistics

Panel A presents summary statistics across stock-day observations. Panel B sums variables by day and then averages across days. The variables are *users_close* (last observed user count for a stock prior to the 4 pm ET close), *users_last* (last user count of the day), *userchg* (daily change in *users_close*), *userratio* ($users\_close(t)/users\_close(t-1)$), *prc* (closing price), *size* (market cap in millions), *ret* (daily return), *openret* (overnight return), *dayret* (daytime return), *daily_buys* (number of TAQ daily retail buys), *daily_sells* (number of TAQ daily retail sells), *net_buys* ($daily\_buys - daily\_sells$), *taq_retimb* ($net\_buys/(daily\_buys + daily\_sells)$), and *#stocks* (number of stocks with users reported on Robintrack).

Variable	*N*	Mean	*SD*	min	p25	p50	p75	max
				Panel A: Stock-Day Observations				
users_close	3,952,749	2,064.27	15,422.64	0.00	35.00	160.00	674.00	990,059.00
users_last	4,067,791	2,061.48	15,419.80	0.00	35.00	160.00	673.00	990,587.00
userchg	3,851,419	9.46	245.07	−19,643.00	−1.00	0.00	1.00	85,193.00
userratio	3,745,652	1.01	0.32	0.00	1.00	1.00	1.01	263.67
prc	3,765,043	52.47	1,828.84	0.04	10.38	23.71	46.81	344,970.00
size ($mil)	3,625,145	5,674.62	29,154.96	0.00	108.25	498.94	2,416.15	1,581,165.00
ret (%)	3,764,157	0.04	4.21	−91.79	−0.98	0.02	0.99	897.73
openret (%)	3,674,652	0.10	2.64	−88.60	−0.40	0.03	0.55	563.90
dayret (%)	3,696,846	−0.05	3.41	−87.59	−0.91	0.00	0.78	841.18
daily_buys	3,586,637	200.69	1,112.99	0.00	9.00	34.00	117.00	185,930.00
daily_sells	3,586,637	178.97	875.49	0.00	8.00	34.00	115.00	113,152.00
net_buys	3,586,637	21.72	367.93	−30,246.00	−7.00	0.00	10.00	86,640.00
taq_retimb	3,585,659	0.01	0.35	−1.00	−0.14	0.00	0.16	1.00
				Panel B: Daily Observations (Summed Variable Averaged across Days)				
#stocks	549	7,211.01	741.42	5,805.00	6,559.00	7,199.00	8,054.00	8,131.00
users_close (mil.)	549	14.86	9.93	1.32	8.27	11.83	15.22	42.14
users_last (mil.)	549	14.89	9.93	5.58	8.27	11.83	15.23	42.16
userchg (000)	535	68.11	112.57	−48.83	14.70	23.74	54.11	810.40
daily_buys (000)	549	1,276.35	739.49	387.97	824.86	923.12	1,297.50	3,952.49
daily_sells (000)	549	1,137.28	585.45	360.04	778.65	872.51	1,181.31	3,174.90
net_buys (000)	549	139.07	171.91	−67.98	38.44	63.30	133.80	1,005.84

Table II

Summary Statistics for Robinhood Herding Events

This table provides summary statistics for stock-days associated with herding events, defined as securities in the top 0.5% of positive user change ratio on day t and a minimum of 100 users on day $t-1$. The variables are *users_close* (last observed user count for a stock prior to the 4 pm ET close), *users_last* (last user count of the day), *userchg* (daily change in *users_close*), *userratio* (*users_close*(t)/*users_close*($t-1$)), *prc* (closing price), *size* (market cap in millions), *ret* (daily return), *openret* (overnight return), *dayret* (daytime return), *daily_buys* (number of TAQ daily retail buys), *daily_sells* (number of TAQ daily retail sells), *net_buys* (*daily_buys* − *daily_sells*), and *taq_retimb* (*net_buys*/(*daily_buys* + *daily_sells*)).

Variable	N	Mean	SD	min	p25	p50	p75	max
users_close	4,884	2,487.02	7,573.30	116.00	353.00	774.50	1,914.50	154,351.00
users_last	4,884	2,605.28	7,887.32	118.00	367.00	810.00	2,007.50	156,826.00
userchg	4,884	1,103.72	3,514.05	16.00	119.00	288.50	803.00	85,193.00
userratio	4,884	1.99	1.69	1.10	1.37	1.56	1.98	44.71
prc	4,712	163.89	6,973.02	0.12	3.34	8.95	21.39	341,000.00
size ($mil)	4,299	2,231.98	11,532.14	0.11	45.29	375.29	1,229.05	468,894.20
ret (%)	4,711	14.02	52.58	−91.79	−7.10	4.88	20.56	874.84
openret (%)	4,707	10.99	39.19	−88.60	−0.94	2.04	11.61	563.90
dayret (%)	4,710	3.43	30.68	−74.69	−7.79	−0.06	8.02	595.19
daily_buys	4,675	3,498.46	9,536.55	0.00	252.00	774.00	2,669.00	162,678.00
daily_sells	4,675	2,710.01	7,108.48	0.00	205.00	615.00	2,149.00	110,145.00
net_buys	4,675	788.44	2,962.92	−8,873.00	7.00	98.00	487.00	56,504.00
taq_retimb	4,675	0.11	0.17	−0.75	0.01	0.09	0.20	1.00

identify Robinhood herding events, we first identify stocks with an increase in users (i.e., *userratio*(t) > 1) and at least 100 users entering the day (i.e., *users_close*($t-1$) ≥ 100). We then sort these stocks based on the day t *userratio* and identify the top 0.5% of stocks as Robinhood herding stocks, which we denote with the indicator variable *rh_herd*. This procedure results in a sample of 4,884 herding events (about nine per day on average) for 2,301 unique tickers.

Table II presents descriptive statistics on the sample herding events across stock-day observations. The average stock in these episodes has about 2,500 users and experiences an increase in users of 1,100. The return on the stock on the day of such episodes is on average 14%, with most of the return occurring at the open of trading—the mean opening return (*openret*) is 11%. Despite these large positive mean daily returns, however, we also observe stocks (about 1/3) with large negative returns on these herding event days. As we point out below, the appeal of large negative stocks may be due in part to the Robinhood app, which highlights "Top Movers" for the day based on absolute rather than signed returns, that is, unlike many stock lists that focus on the most positive movers for the day, the Robinhood app focuses users' attention on stocks with extreme returns. We tend to observe a large retail order imbalance in TAQ on these days as well, which is not surprising since Robinhood trades are a subset of TAQ trades.

II. Attention and Stock Selection

In the first part of our analysis, we document that Robinhood users show excessively concentrated trading activities, compared with the general population of retail investors as captured by the TAQ data set. We then show that attention measures strongly predict Robinhood herding episodes and use the model to forecast the probability of herding episodes for individual stocks. To convincingly show that Robinhood users are particularly prone to trading in attention-grabbing stocks, we exploit Robinhood trading outages and document sharper drops in retail volume for stocks with a high probability of a herding episode during these outages. In a final analysis, we show that unique features of the Robinhood platform predict the trading of Robinhood users more strongly than other retail investors, which suggests that the app itself guides user decisions.

A. The Concentration of Buying versus Selling

In theory, attention-induced trading should predominantly affect purchase rather than sale decisions—retail investors can buy any stock that captures their attention but can only sell stocks that they own (unless they sell short, which is relatively uncommon among retail investors and not possible on the Robinhood platform). We expect attention-motivated trading to be common among Robinhood users. To test this conjecture, we compare the concentration of buying activity to the concentration of selling activity for Robinhood users. We also expect the concentration of buying to be greater for Robinhood users than the general retail investor population. While attention certainly affects the general population of retail investors, we expect other motives to play a greater role in their trading decisions (e.g., trade to rebalance, harvest tax losses, diversify, or save/consume rather than engage in attention-motivated trading). This is especially true since half of Robinhood users are new investors, who are more subject to attention biases (Seasholes and Wu (2007)).

To empirically investigate these questions, we first identify the 10 stocks with the most Robinhood-buying activity on each day (i.e., largest Robinhood user changes). We then calculate the concentration of buying among these 10 stocks as the total number of new users for these stocks divided by sum of user increases for all stocks with an increase in users. Similarly, we identify the 10 stocks with the most TAQ retail buying (i.e., largest net buying based on number of retail buys minus number of retail sells). We then calculate the concentration of buying among these 10 stocks as the total number of net buys for these stocks divided by sum of net buying for all stocks with net buying (i.e., a positive order imbalance). These calculations are repeated for each day, yielding a time series of daily measures of buying concentration for Robinhood and TAQ retail investors. We also perform an analogous calculation for negative user changes on Robinhood and TAQ net selling.

Figure 2 presents the mean concentration of buying (Panel A) and selling (Panel B) for Robinhood users (green bars) and TAQ retail trades (white bars).

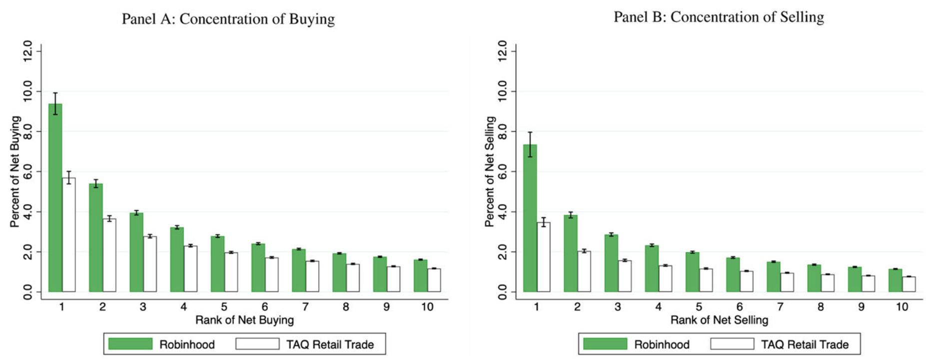

Figure 2. The concentration of buying and selling. In Panel A, the figure depicts the mean daily percent of net buying that is observed in the stock with ranks from 1 to 10, with the rank of 1 corresponding to stocks with the most net buying. In Panel B, the figure depicts the mean daily percent of net selling that is observed in the stock with ranks from 1 to 10, with the rank of 1 corresponding to stocks with the most net selling. Whiskers depict 95% confidence intervals based on standard errors across days. In Robinhood, net buying is user changes. In TAQ, net buying is retail buys less retail sells. (Color figure can be viewed at wileyonlinelibrary.com)

Consistent with the idea that attention has a bigger effect on buying than selling, we find that for both Robinhood and TAQ retail traders, the concentration of buying (Panel A) is higher than the concentration of selling (Panel B). However, both buying and selling concentrations are stronger for Robinhood investors than for the general population of retail traders.[22]

In Table III, we summarize the mean percentage of trades observed in the top 10 stocks and calculate mean daily Herfindahl-Hirschman (HH) indexes for buying (Panel A) and selling (Panel B). For Robinhood users (TAQ retail trades), about 35% (24%) of all net buying is in the top 10 stocks, while 25% (14%) of selling is concentrated in the top 10 stocks. The HH indexes for buying are larger than those observed for selling for both Robinhood and TAQ, which indicates that, in general, the concentration of buying activity is higher than the concentration of selling activity for retail traders. Moreover, the HH indexes for Robinhood are greater than those for TAQ for both buying and selling, which indicates a higher degree of buying and selling concentration for Robinhood users.

One concern with the analysis above is that Robinhood user changes (new owners of the stock) do not map perfectly to TAQ net buying. Essentially, we assume that measures of new owners and net buying generate similar concentration statistics. While we cannot compare the concentration of new owners and net buying in the Robinhood (or TAQ) data set, we can examine this issue using the discount broker trade and position data of Barber and Odean (2000). To do so, we use these data to calculate two variables: daily new users for each stock (from daily positions) and daily order imbalance for each stock

[22] This conclusion assumes that there is no bias in the Boehmer et al. (2021) methodology that would affect concentration measures.

Table III

Concentration of Retail Buying and Selling

The sample consists of stocks with a measure of Robinhood user changes and net retail buying in TAQ. Statistics are based on averages across days. In Panel A, *HH_buy* is the Herfindahl-Hirschman index for stocks with net buying (sum of squared share of buying) and *Top*10*_buy* is the percentage of all net buying in the 10 stocks with the highest level of net buying. In Panel B, *HH_sell* is the Herfindahl-Hirschman index for stocks with net selling (sum of squared share of selling) and *Top*10*_sell* is the percentage of all net selling in the 10 stocks with the highest level of net selling. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

	Robinhood User Changes	TAQ Retail Trades	Difference (RH − TAQ)
Panel A: Mean Daily Concentration Measures among Stocks with Net Buying			
HH_buy (bps)	246.952***	110.820***	136.133***
	(13.091)	(5.575)	(11.433)
*Top*10*_buy* (%)	34.621***	23.560***	11.061***
	(0.412)	(0.315)	(0.361)
Panel B: Mean Daily Concentration Measures among Stocks with Net Selling			
HH_sell (bps)	172.760***	48.566***	124.194***
	(20.069)	(2.357)	(20.055)
*Top*10*_sell* (%)	25.370***	14.076***	11.294***
	(0.369)	(0.218)	(0.384)

(from trades). The correlation between these two series is 87%; they generate concentration statistics in the broker data that differ by less than 0.5% at the individual stock level. Given the differences in concentration that we observe in Table III and Figure 2, we conclude that the differences are not due to measurement differences and therefore Robinhood users' purchase activity is indeed more concentrated than the general population of retail traders.

B. Attention Proxies and Robinhood Herding Events

If attention is guiding the trading decisions of Robinhood investors, we expect proxies for investor attention to be strong predictors of Robinhood herding episodes. Here, we examine the relation between a set of attention measures and the herding episodes we study. While this analysis is interesting on its own, the model also identifies stocks that are at high risk of a herding episode, which is useful for our analysis of retail trading during Robinhood outages below. To begin, we estimate a linear probability model by regressing the extreme herding episode indicator on a set of attention measures, including extreme absolute lagged returns, lagged abnormal volume, lagged user change, lagged level of users, lagged abnormal Google search volume, lagged abnormal news coverage, and lagged earnings announcement. We process Google search volume index (SVI) following Da, Engelberg, and Gao (2011) and Niessner (2015). We construct the news coverage variable by counting the daily number of news articles written on the ticker based on data obtained from Thomson Reuters MarketPsych Indices (TRMI). All abnormal measures on day $t-1$ are

Table IV

Determinants of Robinhood Herding Indicator Variable (Top 0.5% of Positive Percentage User Change)

The table examines the determinants that predict the Robinhood herding indicator variable (top 0.5% of positive user change ratio on day t and a minimum of 100 users on day $t-1$) using a linear probability model. $rh\_herd(t-1)$ is the lagged Robinhood herding indicator. Extreme absolute return $(t-1)$ is an indicator that equals one if the absolute return is ranked in the top 20 on day $t-1$. Abnormal *Vol* $(t-1)$ is the logarithm of the ratio of stock market volume on day $t-1$ to the average volume from days $t-21$ to $t-2$. User Change $(t-1)$ is the change in Robinhood users from day $t-2$ to day $t-1$. $ln(Users(t-1))$ is the logarithm of Robinhood users before the market closes on day $t-1$. Abnormal *SVI* $(t-1)$ is the logarithm of the ratio of Google search volume on day $t-1$ to the average Google search volume from days $t-21$ to $t-2$. Abnormal News $(t-1)$ is the logarithm of the ratio of news article count on day $t-1$ to the average news article count from days $t-21$ to $t-2$. Earnings Announcement $(t-1)$ is an indicator that equals one if the firm has an earnings announcement on day $t-1$. Robust standard errors are clustered by day and stock level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

	$rh\_herd(t)$			
	(1)	(2)	(3)	(4)
$rh\_herd(t-1)$	0.106***	0.103***	0.102***	0.102***
	(0.005)	(0.005)	(0.005)	(0.005)
Extreme absolute return $(t-1)$	0.0505***	0.0494***	0.0485***	0.0486***
=1: top 20 absret; =0: otherwise	(0.003)	(0.003)	(0.003)	(0.003)
Abnormal *Vol* $(t-1)$	0.000551***	0.000453***	0.000368***	0.000348***
$= ln(Vol(t-1)/AvgVol(t-21, t-2))$	(0.000)	(0.000)	(0.000)	(0.000)
User change $(t-1)$ (in 000s)		0.00806***	0.00738***	0.00733***
		(0.001)	(0.001)	(0.001)
$ln(Users(t-1))$		0.000193***	0.000170***	0.000166***
		(0.000)	(0.000)	(0.000)
Abnormal *SVI* $(t-1)$			0.000149***	0.000142***
$= ln(SVI(t-1)/AvgSVI(t-21, t-2))$			(0.000)	(0.000)
Abnormal news $(t-1)$			0.00195***	0.00107***
$= ln(News(t-1)/AvgNews(t-21, t-2))$			(0.000)	(0.000)
Earnings announcement $(t-1)$				0.00875***
				(0.001)
Observations	3,792,584	3,792,584	3,792,584	3,792,584
R^2	0.022	0.022	0.023	0.023

computed as the logarithm of the ratio of the value on day $t-1$ to the average from day $t-21$ to $t-2$. The lagged herding indicator is also included in the regression to capture persistence in the herding episodes. Robust standard errors are clustered by day and stock level.

Table IV presents the results. We find evidence of persistence in the herding episodes. The coefficient on the lagged herding indicator is positive and statistically significant. A stock that is heavily bought by Robinhood investors is 10% more likely to experience another episode the next day. This is not surprising—the herding episode itself may generate discussion and attract attention through media or social media platforms and lead to additional herding the next day. Moreover, consistent with our results that Robinhood investors respond to the Top Movers list, we find that if a stock's absolute return is ranked in the top 20, the probability of this stock being heavily bought the next day increases by about 5%, significant at 1% level. In addition, the other attention measures all show a higher probability of heavy buying activities on Robinhood.

Taken together, the results show that the extreme herding episodes of Robinhood investors are persistent and can be predicted by various attention measures. We next use the predicted values from these specifications to capture the attention-driven component of the extreme herding episodes in our analyses of Robinhood outages.

C. The Effect of Robinhood Outages on Retail Trading

In this section, we build on the linear probability model of the prior section to establish the importance of Robinhood user trading in attention-grabbing stocks. To do so, we exploit three unexpected trading outages on the Robinhood user platform. These outages allow us to estimate the impact of Robinhood trading on retail trading in general. More importantly, the outages allow us to demonstrate a sharper drop in retail trading for stocks that are good candidates for the herding events we study or that are popular among Robinhood users. This evidence supports our claim that Robinhood users are more likely to engage in attention-induced trading than other retail investors.

To identify Robinhood outages, we review the incident history on Robinhood websites. Three outages affected equity trading, on March 2, March 3, and June 18, 2020. The most prolonged outage occurred on March 2 and lasted virtually the entire trading day (posted as under investigation at 9:38 am ET and as resolved at 2:13 am ET on March 3). On March 3, there was another outage at 10:04 am ET posted as under investigation with service partially restored at 11:35 am ET and fully restored at 11:55 am ET. The third outage occurred on June 18 and began at 11:39 am ET (posted as under investigation) with improvement at 12:43 pm ET (posted as "starting to see improvement") and resolution at 1:08 pm ET.

To estimate the economic impact of Robinhood trading, we use these outages, which are arguably exogenous events that prevent Robinhood users from trading but have no effect on retail investors who trade using other brokers.[23] Specifically, we measure the proportion of retail trading relative to all trading at hourly intervals during the trading hours (i.e., 9:30 am to 4:00 pm ET, with the first interval spanning 9 to 10 am ET). Retail trades are identified in TAQ as in Boehmer et al. (2021).

Figure 3 shows the mean proportion of retail trading for the 50 most popular stocks on Robinhood during these key outage events. Outages are depicted

[23] One might be concerned that unusually heavy volume caused the Robinhood outage. We do not think this is a major concern since the March 2 full-day outage has volume that ranks 12th out of the 21 days centered on March 2. March 3 ranks 9th during the same period. June 18 is the lowest-volume day during the 21 days centered on June 18.

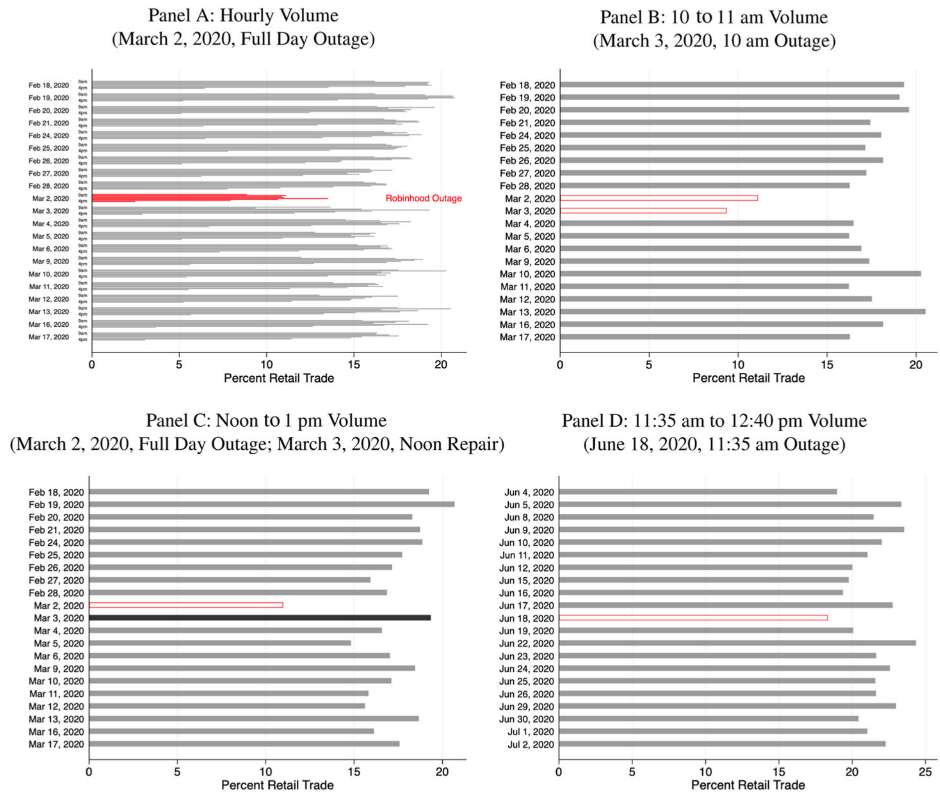

Figure 3. The effect of Robinhood outages on retail trade. In Panels A to C, the sample consists of the 50 most popular Robinhood stocks on February 28, 2020. In Panel A, March 2, 2020, is the day of a Robinhood outage (red bars). In Panel B, March 2, 2020, is the day of a Robinhood outage (white bar). A second shorter outage occurred around 10:00 am on March 3, 2020, and lasted for a bit more than an hour (white bar). In Panel C, March 2, 2020, is the day of a Robinhood outage (white bar). Robinhood tweeted all systems were fully restored at 11:55 am on March 3, 2020 (black bar). In Panel D, the sample consists of the 50 most popular Robinhood stocks as of June 17, 2020. The outage occurs between 11:30 and 12:30 on June 18, 2020 (white bar). (Color figure can be viewed at wileyonlinelibrary.com)

with red bars. In Panel A, the March 2 full-day outage has the lowest percent of retail trade. In Panel B, we see that mean retail trading during the 10 am hour was low on both March 2 (full-day outage) and March 3 (intraday outage). In Panel C, we see that mean retail trading during the noon hour was low on March 2 (full-day outage) but high when trading resumed on Robinhood following an early outage on March 3. In Panel D, we see that mean retail trading between 11:35 am and 12:40 pm ET is low on June 18 relative to other days.

To more formally test for differences, we estimate the following regression for the March 2 day-long outage:

$$RetailPerc_{it} = a + bOutage_t + \mu_{tod} + \mu_{stock} + e_{it}, \tag{1}$$

where $RetailPerc_{it}$ is the percent of trades that are retail trades on TAQ during hour t for stock i, and $Outage_t$ is an indicator variable that takes a value of one on March 2. As controls, we include time of day fixed effects (μ_{tod}) and stock fixed effects (μ_{stock}). The key coefficient estimate, b, measures the percentage point decline in the percentage of total trading during the Robinhood outage period. Standard errors are double clustered by day and stock.

For the intraday outage on March 3, we estimate the regression

$$RetailPerc_{it} = a + bOutage_t + cRepair_t + \mu_t + \mu_{tod} + \mu_{stock} + e_{it}. \tag{2}$$

For this episode, *Outage* is an indicator variable that takes a value of one between 10 and 11 am on March 3, and *Repair* is an indicator variable that takes a value of one between noon and 1 pm (the hour after systems are fully restored).

For the intraday outage on June 18, $RetailPerc_{it}$ is measured at five-minute intervals to estimate

$$RetailPerc_{it} = a + bOutage_t + cPartial_t + dRepair_t + \mu_t + \mu_{tod} + \mu_{stock} + e_{it}. \tag{3}$$

In equation (3), *Outage* takes a value of one for intervals beginning at 11:35 am to 12:35 pm, *Partial* takes a value of one for the intervals beginning at 12:40 to 1:00 pm, and *Repair* takes a value of one for the intervals beginning at 1:05 to 2:00 pm.

Table V summarizes the results. We estimate models for all stocks, the 50 most popular Robinhood stocks, and the 50 highest-attention stocks in columns (1) to (3), respectively. To identify the 50 highest-attention stocks, we use the fitted values from the linear probability model that predicts the Robinhood herding events (column (3), Table IV). In Panel A, we see that the full-day outage on March 2 reduces trading for all stocks by 0.723 percentage points (ppt) ($p < 0.001$), which represents 6% of the average fraction of retail trading (12.10%) during this period. For the 50 most popular Robinhood stocks, retail trading declines by 5.227 ppt ($p < 0.001$), which represents 36% of the average fraction of retail trading (14.60%) for these stocks. For the 50 high-attention stocks, we observe a 4.948 ppt decline in trades, which represents a 28% decline in the typical level of retail trades for these stocks (17.68%).

For the intraday outage of March 3, we observe similar patterns and magnitudes during the outage period. However, we also observe detectable rebounds in trading in the first hour after the outage was resolved, suggesting that the outage generated some pent-up demand to trade among retail investors. For the intraday June 18 outage, we observe similar patterns but somewhat smaller magnitudes.[24]

[24] In Figure IA1, we show five-minute mean trading during the 11:35 am to 12:40 pm interval. Trading volume increases noticeably at the end of this interval. We do not know if this is random

Table V

The Effect of Robinhood Outages on Percent Retail Trade

The dependent variable is the proportion of TAQ trades that are identified as retail trades per period. *Outage* is an indicator variable that takes a value of one at the time of an outage. In Panels B and C, *Repair* is an indicator variable that takes a value of one for the hour after systems are fully operational. In Panel C, *Partial* is an indicator variable that takes a value of one for the period in which systems are partially restored. Column (1) presents results for all stocks; column (2) for the 50 most popular Robinhood stocks, and column (3) for the 50 high-attention stocks (based on fitted values of model 3, Table IV). In Panel A, the Robinhood outage is for the full day on March 2, 2020, and observations are stock-hours. In Panel B, the Robinhood outage starts March 3, 2020 at 10:15 am, with all systems back online sometime between 11 am and noon; observations are stock-hours. The data set for Panels A and B spans February 18 to March 17. In Panel C, the Robinhood outage starts June 18, 2020, at 10:39 am, with systems improvement at 12:43 pm and fully restored at 1:08 pm. The data set for Panel C spans June 4 to July 2. *Outage* is an indicator variable that takes a value of one for the time intervals between 11:35 am and 12:35 pm, June 18; observations are stock-five-minute periods. Robust standard errors are double clustered by day and ticker. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

	All Stocks	50 Popular Stocks	50 High Attention Stocks
	Panel A: March 2 Outage (All Day)		
Outage	-0.723^{***}	-5.227^{***}	-4.948^{***}
	(0.203)	(0.338)	(0.340)
Observations	1,090,382	8,395	8,319
R^2	0.393	0.745	0.618
Day FE	NO	NO	NO
Ticker FE	YES	YES	YES
Time of Day FE	YES	YES	YES
	Panel B: March 3 Outage (Late Morning)		
Outage	-1.720^{***}	-6.610^{***}	-5.122^{***}
	(0.172)	(0.712)	(0.550)
Repair	1.581^{***}	3.742^{***}	1.652^{***}
	(0.133)	(0.131)	(0.124)
Observations	1,038,326	7,997	7,821
R^2	0.397	0.764	0.614
Day FE	YES	YES	YES
Ticker FE	YES	YES	YES
Time of Day FE	YES	YES	YES
	Panel C: June 18 Outage (Late Morning)		
Outage	-0.678^{***}	-3.042^{***}	-0.752^{**}
	(0.067)	(0.455)	(0.350)
Partial	0.476^{***}	1.005^{***}	0.973^{**}
	(0.091)	(0.312)	(0.346)
Repair	0.731^{***}	1.543^{***}	0.458^{***}
	(0.092)	(0.190)	(0.145)
Observations	9,443,439	81,814	64,652
R^2	0.231	0.621	0.176
Day FE	YES	YES	YES
Ticker FE	YES	YES	YES
Time of Day FE	YES	YES	YES

In summary, the analysis of outages shows that Robinhood users account for as much as 6.6% of total trades in stocks (and one-third of retail trades) in the 50 most popular Robinhood stocks. Perhaps more importantly for our purposes, the analysis reveals that Robinhood users are particularly active in high-attention stocks, accounting for as much as 6.5% of total trading in these stocks (and more than one-fourth of total retail trading). The latter result lends credibility to our assumption that the analysis of Robinhood trading is a good proxy for attention-motivated trading. These magnitudes are also consistent with the June 2020 DARTs data suggesting that Robinhood represents approximately 30% of retail trades.

D. The Robinhood User Interface and Stock Selection

One potential driver for the excessively concentrated trading on Robinhood could be the coordination of common signals. Given individuals' aversion to complexity (Oprea (2020), Umar (2020)), Robinhood employs a simple platform design to reduce the cognitive hurdles to financial decision making. Its simplified interface is in striking contrast with traditional brokerage firms, which provide investors a rich set of indicators and research tools. For example, besides basic market information, Robinhood provides only five charting indicators, while TD Ameritrade provides 489.[25] Presented with a large variety of stimuli, investors using traditional investing products are likely to have heterogeneous responses given the limited capacity and highly flexible allocation of human attention (Kahneman (1973)). In contrast, the reduced number of stimuli on Robinhood makes it easy for investors to focus their attention and is likely to generate coordinated attention-induced responses.

In this section, we analyze the effect of Robinhood's lists on investor's trading. These lists are displayed prominently on the platform and are easily accessible under "News/Popular Lists." The two most prominently displayed lists are the "Most Popular" list and the Top Movers list. We focus on the Top Movers list because it is short and constantly changing, while the Most Popular list is long and largely static. The Top Movers list includes stocks with the day's largest percent gains and losses since the market close the previous day.

D.1. Top Movers' Absolute Return Feature

The default sorting of the Top Movers list is based on absolute returns and thus mixes top gainers and top losers.[26] This feature differs from almost all other media accounts (e.g., *Wall Street Journal*, Yahoo! Finance, CNBC, etc.)

or perhaps a result of Robinhood systems being partially operational before the posted time on their website.

[25] See https://www.stockbrokers.com/compare/robinhood-vs-tdameritrade.

[26] Figure IA2 provides an example of the Top Movers list on October 8, 2020, as shown on the website. The initial screen shows four top-ranked stocks by absolute returns, which includes three top gainers and one top loser.

that also report the top movers, but separate the top gainers and top losers rather than mix them together.

We exploit this unusual feature of Robinhood's Top Movers list and compare the buying activity between Robinhood investors and general retail investors measured by TAQ data. Given the top gainers and top losers are displayed in the same list on Robinhood, we would expect the degree of availability for the two groups of stocks to be similar for Robinhood investors. As a result, the buying activity of Robinhood investors would not differ much between top gainers and top losers. In contrast, the top losers are less prominently displayed on other media accounts, where they are reported separately from the top gainers. Accordingly, we would expect general retail investors to respond less strongly to top losers than to top gainers.

Figure 4 presents graphical evidence for the comparison. We measure the buying activity of Robinhood investors by intraday user change[27] and the buying behavior of retail investors by TAQ intraday retail net purchases (i.e., number of buyer-initiated retail trades minus seller-initiated retail trades).[28] In Panel A, we rank stocks based on absolute overnight returns from the market close of day $t-1$ to the market open of day t. We measure buying activity on day t,[29] subsequent to ranking. The graph on the left shows how the buying activity of Robinhood users on day t varies with the rank of the 20 stocks with the highest absolute value of overnight returns (i.e., the 20 highest Top Movers); the graph on the right shows buying activity for retail investors. We plot the mean Robinhood intraday user change and TAQ net retail buying for the top 20 movers separately for stocks with positive returns (top gainers) and stocks with negative returns (top losers).

Stocks with bigger absolute price changes are bought more by both Robinhood users and retail investors. This is consistent with evidence of attention-based buying documented in Barber and Odean (2008). Robinhood investors respond similarly to top gainers and losers, while other retail investors buy top gainers much more aggressively than top losers. This is consistent with our hypothesis that the attention of Robinhood users is directed to both top winners and top losers because both appear on the Top Movers list, while the attention of other investors is directed more to stocks that appear on top gainers lists. In a robustness test, Panel B sorts top movers on the daily close-to-close return and shows similar patterns.

[27] Since the algorithm by Boehmer et al. (2021) cannot identify retail trades at the open auction, for this analysis we exclude the user change at the open on Robinhood to make the Robinhood user change more comparable with TAQ net retail buying.

[28] Since Robinhood does not allow short selling, to make TAQ net retail buying more comparable with the Robinhood user change, we remove short trades from TAQ following Boehmer and Song (2020). The results are similar with or without short trades removed from TAQ.

[29] We do not have the actual Top Mover list as it appears on Robinhood but use the return ranks as a proxy for whether a stock is likely to appear on the list. Accordingly, we only rank stocks with market cap greater than $300 million, since Robinhood only ranks stocks above this size threshold to create the Top Mover list.

Panel A: Top Mover Rankings Sorted on Absolute Overnight Return

Panel B: Top Mover Rankings Sorted on Absolute Daily Return

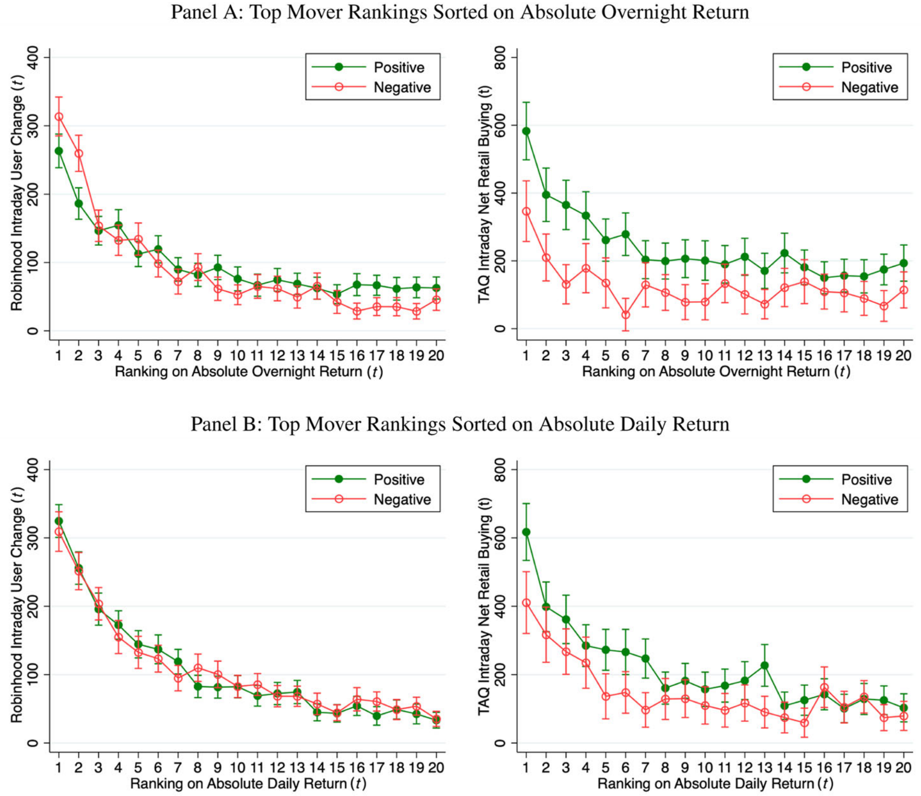

Figure 4. Mean Robinhood intraday user change versus TAQ intraday net retail buying on top mover rankings. The panels present the mean Robinhood intraday user change and TAQ intraday net retail buying of day t against top mover rankings based on different measures. The rankings are sorted for stocks with market cap above \$300 million at the market open of day t. Panel A sorts top movers on absolute overnight returns of day t; Panel B sorts top movers on absolute daily returns of day t. RH intraday user change measures the change in Robinhood users from first time stamp that excludes market open trades to the last time stamp before the market closes. TAQ intraday net retail buying is TAQ retail buying minus TAQ retail selling (with short trades removed following Boehmer and Song (2020)) during market trading hours. The error bar represents the 90% confidence interval for the mean. (Color figure can be viewed at wileyonlinelibrary.com)

To more formally test whether the difference is statistically significant between Robinhood intraday user change and TAQ intraday net retail buying, we estimate

$$NetBuy_{it} = \beta_0 + \beta_1 Score_{it} + \beta_2 I_{R_{it}<0} + \beta_3 Score_{it} \times I_{R_{it}<0} + \alpha_t + \varepsilon_{it}, \quad (4)$$

where the dependent variable is Robinhood or TAQ buying activity for stock i on day t, and $Score_{it}$ assigns a score to each rank of top movers. For expositional ease, we assign 20 to the stock with highest absolute returns and 1 to the stock with the 20th highest absolute returns, so scores increase with the absolute returns. The variable $I_{R_{it}<0}$ is an indicator that equals one if the stock return is negative. For each day, we include only the top 20 movers in the regression. Day fixed effects are included, and robust standard errors are clustered at the daily level. We hypothesize that while other retail investors are less likely to buy top losers than top gainers, Robinhood investors are not.

In Table VI, columns (1) and (2) sort top mover scores on absolute overnight returns. The buying activity increases with top mover scores in both columns. This result indicates that, for both Robinhood investors (column (1)) and general retail investors (column (2)), attention is affected by the ranks within the top movers, with higher ranks making stocks more salient.

The key difference in the buying activity of Robinhood investors and general retail investors is reflected by the coefficient on the indicator for negative returns (or, top losers). For general retail investors, the top losers garner much less buying activity than the top gainers. Within the same rank, the TAQ net retail buying decreases by 133.2 trades for a top loser versus a top winner, which is similar to the decrease associated with the rank of a top gainer dropping by 10 ($\approx 133.2/13.41$). In addition, the interaction of the top rank and negative return is negative indicating the magnitude of negative return effect is larger for the more extreme returns. This pattern differs from that of Robinhood investors. If anything, Robinhood buying activity is slightly stronger for the top losers than for the top gainers and the interaction effect is positive. Columns (3) and (4) sort top mover scores on absolute daily returns and find similar results for the general population of retail traders.

An alternative explanation for the differences between Robinhood and TAQ shown in Figure 4 and Table VI could be a different combination of positive feedback traders versus contrarians between Robinhood and general retail investors. Under this explanation, investors simply respond to extreme price movements rather than the information display. Here, there are two distinct types of traders: positive feedback traders who respond positively to extreme past returns and contrarians who respond negatively to extreme past returns. If the two groups of investors are evenly distributed in Robinhood while positive feedback traders dominate among general retail investors, we would observe the patterns shown in Figure 4 and Table VI. To address this concern and provide additional evidence of the app's influence on Robinhood users, in the next section we explore another unique feature of the Top Movers list.

D.2. Market Cap Requirement for Top Movers

In this section, we exploit a regression discontinuity design to further establish the causal impact of the app interface on investors' trading behavior. Ideally, one would consider a regression discontinuity design that exploits the threshold between the 20th and 21st top mover stocks. However, as we do not observe the actual ranking of price swings and the ranking is likely to change throughout the day, the noise potentially introduced by using approximated rankings may be too large to result in clean identification.

Table VI

The Effect of Top Movers on Robinhood Intraday User Change versus TAQ Intraday Net Retail Buying

The table examines how the top mover rankings affect Robinhood (RH) intraday user change and TAQ intraday net retail buying. The rankings are sorted for stocks with market cap above $300 million at the market open of day t. The stocks are sorted on absolute overnight return (columns (1) and (2)) and absolute daily return (columns (3) and (4)), respectively. The sample requires both Robinhood user change and TAQ net retail buying be available and only includes the top 20 stocks for each day. RH intraday user change measures the change in RH users from first time stamp that excludes market open trades to the last time stamp before the market closes. TAQ Intraday Net Retail Buying is TAQ retail buying minus TAQ retail selling (with short trades removed following Boehmer and Song (2020)) during market trading hours. Top mover score assigns a score for each rank, with 20 for the highest absolute return and 1 for the 20th highest. Negative return is an indicator variable that equals one if the stock return is negative. Regressions include day fixed effects. Robust standard errors are clustered by day. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Top Mover Score is Sorted on:	Absolute Overnight Return (t)		Absolute Return (t)	
	RH Intraday User Change (t) (1)	TAQ Intraday Net Buy (t) (2)	RH Intraday User Change (t) (3)	TAQ Intraday Net Buy (t) (4)
Top mover score	7.198***	13.41***	11.95***	17.89***
=20: highest absret; =1: 20th highest absret	(0.510)	(1.701)	(0.539)	(1.671)
Negative return	46.49***	−133.2***	2.980	−86.90***
=1: top mover return is negative; =0, otherwise	(9.913)	(29.950)	(10.252)	(28.705)
Top mover score × Negative return	3.462***	−6.591***	−1.472**	−6.245***
	(0.736)	(2.369)	(0.724)	(2.222)
Day FE	Yes	Yes	Yes	Yes
Observations	10,247	10,247	10,342	10,342
R^2	0.233	0.211	0.272	0.192

To mitigate this concern, we focus on the market cap requirement for the Top Movers list. Specifically, Robinhood requires that stocks be above \$300 million in market cap to be displayed in the Top Movers list.[30] This feature allows us to employ a sharp regression discontinuity design to study Robinhood investors' responses to extreme price movements of stocks with market cap around the \$300 million cutoff. If the interface does not affect investors' trading behavior, there should not be any discernible differences in investor responses to top mover stocks with market cap above or below the \$300 million cutoff. Our assumption is that any differences in investor responses on either side of the cutoff, after controlling for the effect of market cap, should be due only to the impact of the Robinhood interface on investors' trading behavior.

Specifically, we select top mover stocks with market cap within a small bandwidth (e.g., \$50 million) around the \$300 million cutoff for our regression discontinuity analysis. Given the Robinhood Top Movers list displays the top 20 stocks with market cap above \$300 million that have the largest absolute percentage price moves measured from the previous market close price, we consider our treatment group for day t as stocks with market cap $\in$ (\$300 million, \$350 million] that ranked top 20 by absolute day-t overnight returns ($|R^{Overnight}_{Treatment,\,t}|$) among all stocks with market cap above \$300 million. Our control group then includes stocks with market cap $\in$ [\$250 million, \$300 million] that have absolute day-t overnight returns ($|R^{Overnight}_{Control,\,t}|$) close to stocks in the treatment group.[31] We also vary the bandwidth choices at three other levels (i.e., \$75, \$100, and \$125 million) to test the robustness of our results.

We exploit a sharp regression discontinuity design. Intuitively, this estimation exploits the discontinuity in information display at the \$300 million market cap threshold and tests for discontinuities in investor buying behavior around this threshold. We estimate the following pooled, cross-sectional sharp RD specification:

$$
\begin{aligned}
userchg_{it} = {} & \beta_0 + \beta_1 I_{mktcap_{it} > \$300m} + \sum_{n=1}^{N} \beta_2^n \left(mktcap_{it} - \$300m\right)^n \\
& + \sum_{n=1}^{N} \beta_3^n \left(mktcap_{it} - \$300m\right)^n \times I_{mktcap_{it} > \$300m} + \varepsilon_{it}, \qquad (5)
\end{aligned}
$$

[30] According to Robinhood Web Disclosures (https://cdn.robinhood.com/disclosures/WebDisclosures.pdf), "Robinhood uses a proprietary algorithm to display stocks with a market cap of more than \$300 million that have largest price movements as measured from the previous market close price" for the Top Movers list.

[31] For each stock in the treatment group, we find a matched stock that has the closest absolute return distance with the treated stock among all stocks with market cap $\in$ [\$250 million, \$300 million] that satisfy $0.5 \le |R^{Overnight}_{Treatment,\ t}|/|R^{Overnight}_{Control,\ t}| \le 2$. With the matching, the distributions of the absolute overnight returns are similar between the treatment group (mean: 0.090, median: 0.073, std dev: 0.059) and the control group (mean: 0.078, median, 0.062, std dev: 0.054). We implement the same sharp RD test on the absolute overnight returns in Table IAIII and find no discontinuity in the absolute overnight returns at the \$300 million threshold.

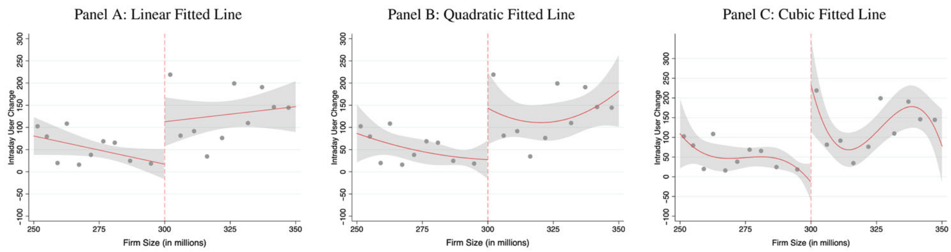

Figure 5. Robinhood intraday user change for top movers around the $300 million market cap cutoff. This figure shows a binned scatterplot for the Robinhood (RH) intraday user change against market cap for stocks included in the regression discontinuity analysis as described in Table VII. The red lines are the linear (Panel A), quadratic (Panel B), and cubic fitted lines (Panel C) estimated separately for market cap above and below the $300 million cutoff. Shaded areas indicate the 90% confidence interval. (Color figure can be viewed at wileyonlinelibrary.com)

where $userchg_{it}$ is the net buying activity of Robinhood investors measured by the intraday user changes on day t, $mktcap_{it}$ is the market cap of stock i at the market open of day t, and $I_{mktcap_{it}>\$300m}$ is an indicator that equals one for stocks with market cap at the market open of day t greater than $300 million. As controls, we include different polynomial functions of market cap ($N = 1, 2, 3$) so that the point estimate on the above-cutoff indicator variable (β_1) is identified under the assumption that the relation between investor trading behavior and market cap is not discontinuous exactly at the $300 million cutoff threshold for reasons besides the app interface.

The regression results in Table VII show a discontinuous increase in Robinhood investors' buying activities when market cap exceeds the $300 million cutoff. The coefficient estimate (β_1) is positive and statistically significant. The results are robust to different bandwidth choices and to including controls for linear, quadratic, and cubic functions of market cap. Graphical evidence corresponding to the three specifications with the $50 million bandwidth is presented in Figure 5. As the figure shows, the intraday user change exhibits a clear jump at the market cap cutoff of $300 million.

To verify that we are not obtaining spurious estimates of the effects of the information display using the regression discontinuity design, we conduct a placebo test exploiting alternative market cap cutoffs at $250 million. For the placebo test using the $250 million cutoff, we select top mover stocks within a $50 million bandwidth around the $250 million cutoff (i.e., market cap ∈ ($200 million, $300 million]) and conduct the same regression estimation. Since none of the stocks in this placebo exercise would be displayed on the Top Movers list by Robinhood, the coefficient estimate on the treatment effects (β_1) should be zero. As shown in the regression results in the Internet Appendix Table IAIV, the coefficient estimate (β_1) is indeed statistically insignificant for the $250 million cutoff.[32]

[32] The Internet Appendix may be found in the online version of this article.

Table VII

Regression Discontinuity in Robinhood Intraday User Change for Top Mover Stocks

This table estimates a sharp regression discontinuity regression that exploits the discontinuity in Robinhood (RH) intraday user changes around the market cap cutoff of $300 million. Specifically, we use RH intraday user changes at day (t) as the dependent variable, and include an indicator that equals one for stocks that have market cap at the market open of day t greater than $300 million. We include different polynomial functions of market cap as controls. Our analysis varies sample bandwidth from Panels A to D. Panel A uses a sample bandwidth of $50 million (i.e., market cap ∈ [$250 million, $350 million]). For stocks with market cap above $300 million, we select stocks that rank top 20 by absolute day-t overnight returns among all stocks with market cap above $300 million. For stocks with market cap below $300 million, we include matched stocks with absolute day-t overnight returns close to stocks with market cap above $300 million. Standard errors are reported in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

	RH Intraday User Change		
	(1)	(2)	(3)
Panel A: Sample Bandwidth = 50 m			
Larger than 300 m	95.71**	115.8**	247.3***
	(39.472)	(53.933)	(78.782)
Polynomial order, N	1	2	3
Observations	1,332	1,332	1,332
R^2	0.013	0.014	0.020
Panel B: Sample Bandwidth = 75 m			
Larger than 300 m	90.57**	109.8*	97.18
	(37.123)	(61.131)	(80.490)
Polynomial order, N	1	2	3
Observations	2,068	2,068	2,068
R^2	0.006	0.006	0.008
Panel C: Sample Bandwidth = 100 m			
Larger than 300 m	77.55**	131.0**	174.8**
	(33.300)	(53.648)	(72.724)
Polynomial order, N	1	2	3
Observations	2,782	2,782	2,782
R^2	0.011	0.011	0.012
Panel D: Sample Bandwidth = 125 m			
Larger than 300 m	49.13*	102.3**	147.7**
	(26.718)	(41.947)	(59.496)
Polynomial order, N	1	2	3
Observations	3,406	3,406	3,406
R^2	0.016	0.016	0.016

Overall, the results in this section are consistent with the idea that the Robinhood app's design impacts the trading decisions of its users.

III. Return Results

Above we find that relative to general retail investors, Robinhood users demonstrate more concentrated buying and selling. Concentrated buying is likely driven by attention and influenced by information display on the Robinhood interface. On days of extreme buying (i.e., herding events), Robinhood users could create price pressure (see Coval and Stafford (2007)). In this section, we examine the return patterns around such herding events.

A. Event-Time Results

Our first analysis in this section examines abnormal returns from day −10 to event day 20 around herding events, where day 0 is the herding day. Abnormal returns are calculated as the stock's return less the value-weighted CRSP index. In Table VIII, we report the mean abnormal return for each day and buy-and-hold abnormal returns (BHARs) separately before and after the event. For example, preevent BHARs are calculated as

$$BHAR_{i\tau} = \prod_{t=\tau-10}^{\tau} (1 + R_{it}) - \prod_{t=\tau-10}^{\tau} (1 + R_{mt}). \tag{6}$$

We also report the percent of returns that are positive.

Standard errors are computed with clustering on the event day since we may have multiple events on the same day. The statistics underlying the mean daily returns therefore rely on the reasonable assumption that returns are serially independent. The longer-horizon abnormal returns are also clustered by event day, which helps corrects for cross-sectional dependence issues. However, the standard errors are likely too small because of the overlapping nature of the returns at longer horizons. We address this econometric concern in the next section with a calendar-time trading strategy.

The BHARs at longer horizons have the advantage that they accurately represent the return earned by investors. Cumulative abnormal returns (the sum of daily abnormal returns) are a positively biased representation of long-horizon abnormal returns in the presence of temporary price pressure effects or bid-ask bounce, both of which are likely issues in the stocks with the herding episodes we study.[33]

[33] To see this, consider a stock that cycles between ask and bid prices of \$10 and \$11 across three days, starting at the \$10 ask. Assume the market return is zero. The daily returns on day 1 are 10% (1/10) and day 2 are −9.1% (−1/11). The daily abnormal returns are 10% and −9.1%. The cumulative abnormal return is 0.9% (10% to 9.1%). The BHAR is zero (11/10 × 10/11–1). While this example uses bid and ask prices for simplicity, the same logic applies to any mechanism that generates negative serial dependence in returns (e.g., temporary price pressure effects or liquidity provision).

Table VIII

Event-Time Abnormal Returns

The table reports abnormal returns around Robinhood user herding events. Abnormal returns (*AR*) are computed as the raw return minus the CRSP value-weighted average return. Abnormal returns are averaged across all events. Buy-and-hold abnormal returns (*BHAR*) are computed as the product of one plus the stock's return through event day *t* less the product of one plus the market return for the same period. Standard errors are computed by clustering on event day. *%Positive* is the percent of returns that are positive. Herding events are defined as the top 0.5% of stocks with positive user change ratio on day 0 and a minimum of 100 users on the prior day. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Event Day	AR	Std. Err.	% Positive	BHAR	Std. Err.	% Positive
			Preevent			
−10	−0.08%	0.14%	47%	−0.08%	0.14%	47%
−9	−0.05%	0.15%	46%	−0.02%	0.27%	46%
−8	0.38%	0.30%	47%	0.22%	0.41%	46%
−7	−0.06%	0.21%	45%	−0.01%	0.50%	45%
−6	−0.28%**	0.13%	46%	−0.48%	0.42%	44%
−5	0.02%	0.15%	48%	−0.47%	0.45%	45%
−4	0.39%*	0.20%	48%	−0.10%	0.50%	46%
−3	0.51%**	0.21%	48%	0.52%	0.59%	47%
−2	0.40%*	0.22%	49%	0.81%	0.60%	48%
−1	4.59%***	0.52%	56%	5.60%***	0.87%	51%
0	13.95%***	0.92%	63%	22.16%***	1.73%	58%
			Postevent			
1	−1.23%***	0.24%	42%	−1.23%***	0.24%	42%
2	−0.85%***	0.18%	42%	−2.11%***	0.31%	40%
3	−0.43%***	0.16%	44%	−2.74%***	0.29%	38%
4	−0.35%**	0.15%	43%	−3.15%***	0.31%	37%
5	−0.32%**	0.14%	44%	−3.55%***	0.32%	37%
6	−0.37%***	0.13%	44%	−3.99%***	0.34%	37%
7	−0.14%	0.14%	46%	−4.17%***	0.37%	36%
8	0.17%	0.17%	45%	−4.13%***	0.39%	36%
9	0.07%	0.13%	45%	−4.19%***	0.40%	36%
10	0.15%	0.16%	45%	−4.15%***	0.40%	37%
11	−0.03%	0.14%	42%	−4.33%***	0.40%	36%
12	−0.03%	0.12%	46%	−4.42%***	0.41%	36%
13	−0.06%	0.13%	44%	−4.51%***	0.43%	36%
14	−0.09%	0.14%	45%	−4.68%***	0.44%	35%
15	−0.15%	0.10%	45%	−4.87%***	0.45%	35%
16	0.03%	0.11%	46%	−4.83%***	0.47%	35%
17	−0.04%	0.14%	45%	−4.76%***	0.56%	35%
18	0.18%	0.22%	46%	−4.71%***	0.56%	35%
19	−0.01%	0.11%	46%	−4.80%***	0.57%	35%
20	0.15%	0.16%	46%	−4.74%***	0.58%	35%

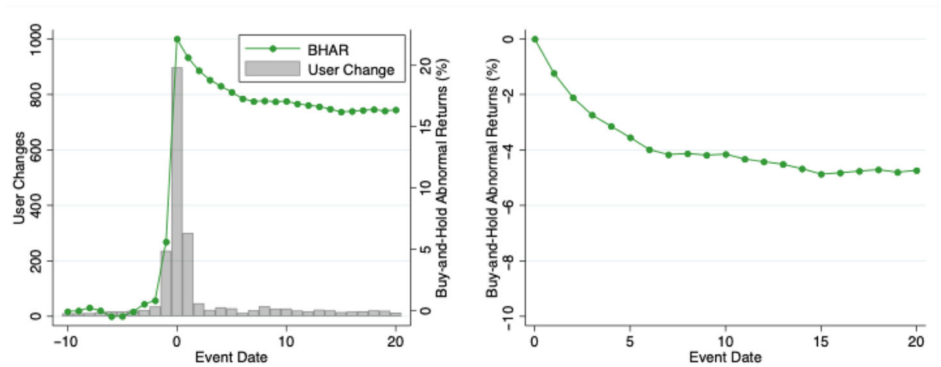

Figure 6. Returns around herding events. The panel on the left depicts mean BHARs and Robinhood user changes from 10 days before to 21 days after herding events. The green line represents BHARs, whereas the gray bars represent user changes. The panel on the right displays postevent mean BHARs starting from day 0. Herding events are defined as the top 0.5% of stocks with positive user change ratio on day 0 and a minimum of 100 users on the prior day. (Color figure can be viewed at wileyonlinelibrary.com)

Prior to the herding event, stocks have abnormal returns near zero. A day or two before the herding event, average returns increase and become statistically significant. The stocks then experience an extremely positive return on the herding day—averaging 14%. Interestingly, many stocks have negative returns the day prior to and on the day of the herding event. This is consistent with our prior results documenting that extreme negative returns draw the attention of Robinhood users as well.

The pattern after the herding events is starkly different. Immediately after the herding event, returns turn significantly negative. After just five days, stocks in the top 0.5% (*rh_herd*) experience negative abnormal returns of −3.5%. By the end of the 20-day period, the return decline totals almost 5%. These results are economically and statistically significant, and are not driven by just a few stocks as almost two-thirds of *rh_herd* stocks have negative cumulative returns by the end of the 20 days.

To visualize these return patterns, in Figure 6 we plot the BHARs for our *rh_herd* events. Results over the entire period are reported in Panel A, and BHARs starting at Day 1 are reported in Panel B. The pattern of returns around herding events is quite clear. Robinhood users are attracted by extreme return events. Their coordinated buying leads to price pressure and then subsequent poor return performance. We also find little evidence of unusual return movement beyond 20 days (see Internet Appendix Figure IA3).

To systematically analyze the relation between the herding intensity and price reversal, we analyze stocks with a minimum of 100 Robinhood users and identify different sets of herding episodes by varying the daily user change ratio from 1.1 to 8.5 (i.e., from a 10% to 750% increase in users holding the stock). Most user change ratios are close to 1.0 (see Table I) and a user ratio of 1.1 corresponds to approximately the 98th percentile of the distribution of user

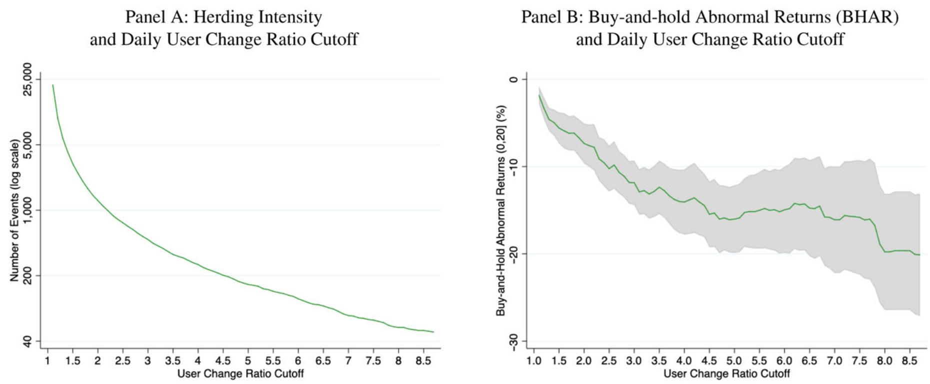

Figure 7. Herding intensity and price reversal. The panels show how herding intensity and 20-day BHARs vary with the daily user change ratio cutoff to identify herding episodes for stocks with at least 100 Robinhood users. Panel A plots the number of herding episodes (in log scale) against the user change ratio cutoff. Panel B plots the 20-day BHARs (%) against the user change ratio cutoff. The daily user change ratio cutoff varies from 1.1 to 8.5. (Color figure can be viewed at wileyonlinelibrary.com)

ratios, so we are analyzing unusual events. For more modest user changes, we observe no relation between returns and the user ratio. In Figure 7, Panel A, we plot the number of herding episodes (y-axis in log scale) against the user change ratio to identify episodes (x-axis). At a user change ratio of 1.1, we observe over 20,000 herding episodes; at a user change ratio of 8.5, we observe 45 episodes. In Panel B, we show that the mean abnormal return following these herding events grows from a statistically significant -1.8% at a user change ratio of 1.1 (>20,000 events or about 36 events per day) to an extremely large -19.6% at a user change ratio of 8.5 or more (45 events or about one event every 12 days). We thus find a clear relation between the magnitude of the buying intensity and the subsequent reversal.

It is possible that the return magnitudes of Figure 7, Panel B, increase as we move to more extreme cutoffs of the user change ratio because the identified stocks become smaller rather than the effect of the herding event. To rule out this size-based explanation, we rerun Figure 7 after throwing out stocks with a market cap greater than \$1 billion, which ensures that mean and median size are the same across the user change ratio cutoffs. We continue to see a dramatic increase in the observed return effects (see Figure IA4, Panel B).

B. Calendar-Time Trading Strategy

To address the cross-sectional dependence issue underlying event-time analyses and to investigate the returns earned on a trading strategy that follows the herding episodes, we construct a calendar-time portfolio that invests \$1 in each herding episode stock at the close of the event day and holds the stock for five days (without rebalancing). We estimate the daily portfolio abnormal return ($alpha$) by regressing the portfolio excess return on the Fama-French five-factor model plus a momentum factor,

$$R_{pt} - R_{ft} = \alpha + \beta \left(R_{mt} - R_{ft}\right) + \sum_{k=1}^{K} c_k F_t^k + e_{pt}, \tag{7}$$

where R_{ft} is the daily risk-free return, R_{mt} is the value-weighted market index, and F_t^k are the $k = 1, K$ factor returns related to size, value, investment, profitability, and momentum (taken from Ken French's online data library). For completeness, we include results with just the market excess return (i.e., the CAPM) and four-factor alphas using market, size, value, and momentum factors.

The results, reported in Table IX, are broadly consistent with the event-time analysis above. Over the sample period, the calendar-time portfolio earns an economically large daily alpha of −55 to −61 bps (columns (1) to (3)), which is in line with the five-day event-time market-adjusted return of −3.55%. We also find that the portfolio alphas are more negative during the 2020 pandemic period, ranging from −78 to −94 bps per day. The Robinhood user changes for herding stocks are also more dramatic during the pandemic period, with a mean (median) *userratio* of 1.75 (1.47) pre-COVID (prior to March 13, 2020) and 2.56 (1.83) post-COVID. However, the return effects of herding events are not unique for the pandemic period, as the negative alphas are also sizable during the pre-COVID period.

C. Regression Results

To further test the return patterns that we explore in event time, we regress daily stock returns for stock i on day t (R_{it}) on lags of the key herding variable (rh_herd) and controls,

$$R_{it} = a + \sum_{k=1}^{5} b_k rh\_herd_{i,t-k} + \sum_{k=1}^{5} c_k taq\_retimb_{i,t-k} + \sum_{k=1}^{5} d_k R_{i,t-k} + \mu_t + e_{it}. \tag{8}$$

The $\{b_k\}$ coefficients estimate the impact of herding events on returns one to five days after the event. We sequentially add groups of control variables to assess how they interact with the herding events that we analyze. Robust standard errors are estimated with clustering by day, which addresses cross-sectional dependence that affects the event-time graphs of the prior section.

Turning to the control variables, we first include lagged retail order imbalance (taq_retimb), which positively predicts returns at short horizons in the United States (Barber, Odean, and Zhu (2008), Kaniel, Saar, and Titman (2008), Kelley and Tetlock (2013), Boehmer et al. (2021)). The retail imbalance variable allows us to assess whether the poor returns we document are a

Table IX

Calendar Portfolio Returns of Herding Events

The dependent variable is the dollar-weighted-average daily return over the risk-free rate (%). For each *rh_herd* event (top 0.5% of positive user change ratio on day t and a minimum of 100 users on day $t-1$), $1/Price$ shares are purchased at the end of the herding day. These stocks are held for five days before being liquidated. Dollar-weighted average daily returns are a dollar-weighted-average of all stocks held based on the position value at the end of the prior day. Returns are over the entire period (columns (1) to (3)), prior to March 2020 (columns (4) to (6)), or March 2020 and after (columns (7) to (9)). The key estimation is the constant, *Alpha*. Control variables include excess market returns ($R_m - R_f$), small-minus-big factor (*SMB*), high-minus-low factor (*HML*), momentum factor (*MOM*), robust-minus-weak operating profitability factor (*RMW*), and conservative-minus-aggressive factor (*CMA*). Robust standard errors are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

	Entire Period			Prior to March 2020			March 2020 and after		
	Daily Excess Return on Dollar-Weighted Calendar Portfolio of Herding Events (%)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Alpha	−0.612***	−0.569***	−0.552***	−0.535***	−0.526***	−0.511***	−0.938***	−0.818***	−0.777***
	(0.112)	(0.110)	(0.108)	(0.118)	(0.118)	(0.118)	(0.305)	(0.284)	(0.273)
Mkt_Rf	0.811***	0.709***	0.660***	0.646***	0.512***	0.437***	0.883***	0.725***	0.699***
	(0.111)	(0.120)	(0.127)	(0.120)	(0.130)	(0.135)	(0.138)	(0.155)	(0.156)
SMB		0.689***	0.446**		0.467	0.332		0.719**	0.399
		(0.218)	(0.219)		(0.308)	(0.304)		(0.317)	(0.384)
HML		0.103	0.355		−0.421*	−0.148		0.298	0.533
		(0.176)	(0.217)		(0.231)	(0.269)		(0.311)	(0.394)
MOM		−0.118	−0.229		−0.511**	−0.599**		0.050	−0.085
		(0.158)	(0.166)		(0.233)	(0.238)		(0.232)	(0.266)
RMW			−0.968***			−0.981***			−0.961
			(0.301)			(0.337)			(0.595)
CMA			−0.773*			−0.703			−0.858
			(0.424)			(0.520)			(0.749)
Observations	555	555	555	448	448	448	107	107	107
R^2	0.190	0.234	0.256	0.056	0.079	0.098	0.407	0.481	0.496

manifestation of general retail order imbalance predicting returns during our sample period.

We also include lagged returns ($R_{i,t-k}$) to control for the well-documented tendency for return reversals at short horizons up to one month (French and Roll (1986), Lo and Mackinlay (1988, 1990), Jegadeesh (1990), Lehmann (1990), Campbell, Grossman, and Wang (1993)) with these effects stronger in volatile markets including the 2020 pandemic period (Nagel (2012), Drechsler, Moreira, and Savov (2020)). These studies speculate that the origins of return reversals may emanate from overreaction, the rewards to providing liquidity provision, and/or more banal microstructure issues (e.g., prices bouncing between bid and ask prices). Attention-motivated trading leads to excessive buying and return reversals following attention-grabbing price increases, so may help explain the returns associated with short-term contrarian strategies. Thus, the inclusion of lagged returns may be overcontrolling as both return reversals and the negative returns we document may have similar origins in attention-motivated trading.

Table X presents results for our herding measure based on the top 0.5% of daily Robinhood user changes. We present results for the full sample of herding events in columns (1) to (3). The last row of the table presents the summed coefficients on the herding indicator variables, which can be interpreted as the five-day abnormal return after the event. These five-day return estimates range from losses of 2.595% to 2.942%. In Table IAV, we use more fine-grained controls for extreme positive and negative return moves and find similar five-day abnormal return estimates derived from the lags of the key *rh_herd* variable.

We separately analyze herding events that occur following a positive or negative overnight return using this regression model.[34] To analyze herding events that follow a positive overnight return, the key indicator variable takes a value of one only if the overnight return (measured from the close on day $t-1$ to the open on day t) is positive and the change in users from the close on day $t-1$ to the close on day t is in the top 0.5% of stocks with positive user changes. The results are presented in columns (4) to (6). The herding events that are preceded by positive overnight returns predict somewhat stronger negative abnormal returns, ranging from −3.025% to −3.909%. We estimate a similar regression conditioning on negative overnight returns in columns (7) to (9). Though smaller in magnitude, we continue to observe negative abnormal returns for those herding events preceded by negative overnight returns, with five-day abnormal returns ranging from −1.490% to −2.341%.

These analyses provide further evidence that attention-motivated trading generates predictable poor returns.

[34] We condition on overnight returns rather than close-to-close returns because overnight returns generally precede Robinhood user changes, which occur most commonly at or after the open of trading. If we condition on close-to-close returns, the herding event might cause the positive returns. When we condition on positive (negative) close-to-close returns, the five-day abnormal return estimated in columns (6) and (9) are −3.375% and −1.887%, respectively (both with $p < 0.01$). See Table IAVI.

Table X

Regression of Daily Returns on Lagged Robinhood Herding Indicator (Top 0.5% Percentage User Change)

The dependent variable is the daily stock return (%) winsorized at the 0.1% level (*ret*). In columns (1) to (3), *rh_herd*(t) is an indicator variable that equals one if the percentage change in users is in the top 0.5% for stocks with positive user changes on day t and a minimum of 100 users on day $t-1$. In columns (4) to (6) (columns (7) to (9)), the *rh_herd*(t) indicator variable equals one if the prior conditions are met and the overnight return from the close on day $t-1$ to the open on day t is positive (negative). Control variables include retail order imbalance from TAQ (*taq_retimb*), lagged returns (*ret*), lags of an indicator variable if the *rh_herd* measure is missing (*rh_herd* is set equal to zero), and day fixed effects. Five-day AR (%) is the sum of the coefficients on the five lags of *rh_herd*. Robust standard errors clustered by day are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

	All Events			Overnight Return > 0			Overnight Return < 0		
	ret(t) (%)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
rh_herd($t-1$)	-1.336^{***}	-1.039^{***}	-1.110^{***}	-1.770^{***}	-1.132^{***}	-1.276^{***}	-0.514^{**}	-0.970^{***}	-0.894^{***}
	(0.160)	(0.171)	(0.174)	(0.215)	(0.256)	(0.260)	(0.209)	(0.226)	(0.229)
rh_herd($t-2$)	-0.758^{***}	-0.813^{***}	-0.798^{***}	-1.148^{***}	-1.235^{***}	-1.212^{***}	-0.152	-0.140	-0.152
	(0.129)	(0.141)	(0.141)	(0.175)	(0.221)	(0.220)	(0.175)	(0.202)	(0.203)
rh_herd($t-3$)	-0.298^{**}	-0.191	-0.183	-0.378^{**}	-0.147	-0.127	-0.268	-0.431^{**}	-0.449^{**}
	(0.122)	(0.134)	(0.132)	(0.160)	(0.202)	(0.199)	(0.194)	(0.208)	(0.207)
rh_herd($t-4$)	-0.318^{***}	-0.266^{**}	-0.266^{**}	-0.322^{**}	-0.169	-0.178	-0.388^{**}	-0.557^{***}	-0.534^{***}
	(0.115)	(0.128)	(0.128)	(0.144)	(0.183)	(0.182)	(0.163)	(0.181)	(0.181)
rh_herd($t-5$)	-0.231^{**}	-0.286^{**}	-0.273^{**}	-0.292^{*}	-0.342^{*}	-0.325^{*}	-0.167	-0.243	-0.237
	(0.117)	(0.131)	(0.131)	(0.152)	(0.190)	(0.190)	(0.166)	(0.171)	(0.171)
ret($t-1$)		-0.046^{***}	-0.037^{***}		-0.045^{***}	-0.036^{***}		-0.047^{***}	-0.038^{***}
		(0.012)	(0.012)		(0.012)	(0.012)		(0.012)	(0.012)
ret($t-2$)		-0.002	-0.002		-0.001	-0.001		-0.003	-0.003
		(0.012)	(0.012)		(0.012)	(0.012)		(0.012)	(0.012)
ret($t-3$)		-0.021^{*}	-0.021^{*}		-0.021^{*}	-0.021^{*}		-0.022^{*}	-0.021^{*}
		(0.012)	(0.012)		(0.012)	(0.012)		(0.012)	(0.012)

(Continued)

Table X—*Continued*

	All Events			Overnight Return > 0			Overnight Return < 0		
	ret(*t*) (%)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$ret(t-4)$		−0.017*	−0.017*		−0.017*	−0.017*		−0.018*	−0.017*
		(0.010)	(0.010)		(0.010)	(0.010)		(0.010)	(0.010)
$ret(t-5)$		−0.005	−0.005		−0.005	−0.005		−0.005	−0.006
		(0.010)	(0.010)		(0.010)	(0.010)		(0.010)	(0.010)
$taq\_retimb(t-1)$			0.043***			0.043***			0.042***
			(0.008)			(0.008)			(0.008)
$taq\_retimb(t-2)$			0.012			0.012			0.010
			(0.008)			(0.008)			(0.008)
$taq\_retimb(t-3)$			0.000			0.000			−0.000
			(0.008)			(0.009)			(0.009)
$taq\_retimb(t-4)$			0.009			0.009			0.009
			(0.008)			(0.008)			(0.008)
$taq\_retimb(t-5)$			0.009			0.009			0.008
			(0.008)			(0.008)			(0.008)
Observations	3,656,926	3,652,401	3,312,553	3,656,926	3,652,401	3,312,553	3,656,926	3,652,401	3,312,553
R^2	0.196	0.199	0.205	0.196	0.199	0.205	0.196	0.198	0.205
Days	550	550	550	550	550	550	550	550	550
Events	4,428	4,412	4,327	2,809	2,800	2,742	1,619	1,612	1,585
Five-day AR (%)	−2.942***	−2.595***	−2.630***	−3.909***	−3.025***	−3.119***	−1.490***	−2.341***	−2.265***
Std. Err.	(0.322)	(0.350)	(0.348)	(0.435)	(0.522)	(0.520)	(0.423)	(0.447)	(0.451)

D. TAQ Herding Events versus Robinhood Herding Events

In the sections above, we employ a herding measure based on Robinhood user changes. In this section, we show that this herding measure is closely related to the herding measure of BLO that is based on TAQ retail trades. BLO document that stocks in the top quintile of retail SOI and the top quintile of abnormal retail volume earn dismal returns over the 2010 to 2019 period.

We adapt the BLO measure to create a sample of TAQ herding events for each day in the Robinhood period that we analyze in this paper. Specifically, on each day, we use the standardized order imbalance (*SOI*) measure of BLO to construct quintiles and identify the stocks in the top quintile of retail order imbalance. Among stocks in this top quintile, we rank stocks based on abnormal retail volume (defined as retail volume on day t divided by mean volume from $t-20$ to $t-1$). We then create an indicator variable (*taq_herd*) that takes a value of one for the N stocks with the greatest abnormal retail volume, with N equal to the number of Robinhood herding events that we identify on day t. Thus, for each day in our sample period, we have an equal number of Robinhood herding events and TAQ herding events.

By construction, we have an equal number of TAQ and Robinhood herding events. More importantly, 27% (1,317 of 4,884) of the stock-day observations are identical. Thus, there is substantial overlap in the herding events identified using Robinhood user changes and the BLO method using TAQ retail trades.

To explore the ability of the two measures to predict future returns, we modify the regression framework of the prior section to include both herding measures. In Table XI, column (1) replicates the main results using the *rh_herd* variable for easy comparison; column (2) uses the identical specification but replaces *rh_herd* with *taq_herd*. We find that *taq_herd* variable also predicts negative abnormal returns, but the magnitudes are smaller (−2.208% vs. −2.942%). (See Tables IAVII, IAVIII, and Figure IA5 for event-time and calendar-time analyses of TAQ herding events.)

In column (3), we add an indicator variable that takes a value of one if TAQ retail order imbalance is positive (*taqpos*) and interact it with *rh_herd*. This analysis shows that the Robinhood herding events reliably predict five-day abnormal returns of −1.506% even when there is no net buying by retail investors in TAQ. The interaction effects (TAQ buying and Robinhood herding) are large and statistically significant, which suggests that the return effects of herding events are larger when the general population of retail investors is also buying. In column (4), we find similar results when we control for lagged returns and order imbalance.

In column (5), we include *rh_herd*, *taq_herd*, and their interactions. These results indicate the *rh_herd* variable generally has larger predictive ability (−2.397% vs. −1.213% for five-day abnormal returns). However, the interaction effects for the two herding variables are not significant, which indicates that the negative returns for events identified by both measures have particularly dismal returns. Recall that 27% (or 1,317) of the events are common, so the

Table XI

Regression of Daily Returns on Lagged Robinhood Herding Indicator and TAQ Retail Herding Indicator

The dependent variable is the daily stock return (%) winsorized at the 0.1% level (*ret*). *rh_herd*(t) is an indicator variable that equals one if the percentage change in users is in the top 0.5% for stocks with positive user changes on day t and a minimum of 100 users on day $t-1$. On each day, we identify the same number of herding events (N) using TAQ retail trade data to construct *taq_herd*(t), an indicator variable that equals one if the stock is among the N stocks with the greatest abnormal retail volume within the top quintile of standardized retail order imbalance on day t. In columns (3) and (4), we include an indicator variable for whether TAQ retail order imbalance is positive (*taqpos*) and its interaction with *rh_herd*. Control variables include retail order imbalance from TAQ (*taq_retimb*), lagged returns (*ret*), lags of an indicator variable if the *rh_herd* measure is missing (and *rh_herd* is set equal to zero), and day fixed effects. Five-day AR (%) is the sum of the coefficients on the five lags of *rh_herd* (or *taq_herd*). Robust standard errors clustered by day are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

	ret(t) (%)					
	(1)	(2)	(3)	(4)	(5)	(6)
rh_herd($t-1$)	-1.336^{***}		-0.549^{**}	-0.514^{**}	-1.001^{***}	-0.838^{***}
	(0.160)		(0.234)	(0.241)	(0.160)	(0.170)
rh_herd($t-2$)	-0.758^{***}		-0.306	-0.358^{*}	-0.550^{***}	-0.587^{***}
	(0.129)		(0.194)	(0.193)	(0.138)	(0.144)
rh_herd($t-3$)	-0.298^{**}		-0.099	-0.086	-0.232^{*}	-0.166
	(0.122)		(0.191)	(0.192)	(0.126)	(0.128)
rh_herd($t-4$)	-0.318^{***}		-0.356^{**}	-0.356^{**}	-0.369^{***}	-0.337^{***}
	(0.115)		(0.159)	(0.162)	(0.112)	(0.120)
rh_herd($t-5$)	-0.231^{**}		-0.196	-0.204	-0.246^{**}	-0.277^{**}
	(0.117)		(0.182)	(0.189)	(0.118)	(0.127)
taq_herd($t-1$)		-1.220^{***}			-0.896^{***}	-0.794^{***}
		(0.154)			(0.151)	(0.182)
taq_herd($t-2$)		-0.772^{***}			-0.485^{***}	-0.536^{***}
		(0.120)			(0.120)	(0.137)
taq_herd($t-3$)		-0.180			0.001	0.147
		(0.113)			(0.107)	(0.125)
taq_herd($t-4$)		0.050			0.173	0.252^{*}
		(0.109)			(0.106)	(0.129)
taq_herd($t-5$)		-0.087			-0.006	-0.022
		(0.100)			(0.106)	(0.124)
rh_herd($t-1$) × *taqpos*($t-1$)			-1.021^{***}	-0.759^{**}		
			(0.300)	(0.310)		
rh_herd($t-2$) × *taqpos*($t-2$)			-0.589^{**}	-0.567^{**}		
			(0.249)	(0.259)		
rh_herd($t-3$) × *taqpos*($t-3$)			-0.260	-0.129		
			(0.239)	(0.263)		
rh_herd($t-4$) × *taqpos*($t-4$)			0.051	0.121		
			(0.213)	(0.223)		
rh_herd($t-5$) × *taqpos*($t-5$)			-0.042	-0.085		
			(0.212)	(0.218)		
rh_herd($t-1$) × *taq_herd*($t-1$)					-0.165	-0.049
					(0.399)	(0.407)
rh_herd($t-2$) × *taq_herd*($t-2$)					-0.252	-0.230
					(0.329)	(0.334)

(*Continued*)

Table XI—*Continued*

	ret(t) (%)					
	(1)	(2)	(3)	(4)	(5)	(6)
$rh\_herd(t-3) \times taq\_herd(t-3)$					−0.262	−0.239
					(0.316)	(0.321)
$rh\_herd(t-4) \times taq\_herd(t-4)$					0.015	0.020
					(0.267)	(0.273)
$rh\_herd(t-5) \times taq\_herd(t-5)$					0.066	0.044
					(0.262)	(0.265)
Observations	3,656,926	3,656,926	3,656,926	3,312,553	3,656,926	3,312,553
R^2	0.196	0.196	0.196	0.205	0.196	0.205
Lagged control variables:						
ret	NO	NO	NO	YES	NO	YES
taq_retimb	NO	NO	NO	YES	NO	YES
taqpos	NO	NO	YES	YES	NO	NO
RH five-day AR (%)	-2.942^{***}		-1.506^{***}	-1.518^{***}	-2.397^{***}	-2.204^{***}
RH Std. Err.	(0.322)		(0.456)	(0.461)	(0.310)	(0.336)
TAQ five-day AR (%)		-2.208^{***}			-1.213^{***}	-0.954^{***}
TAQ Std. Err.		(0.347)			(0.321)	(0.326)

stocks with both a Robinhood and TAQ herding event represent a significant part of the overall sample of Robinhood herding events.

In summary, the Robinhood herding measure that we identify is closely related to the BLO (2021) TAQ herding measure. The Robinhood herding measure has stronger ability to predict short-term negative returns than the TAQ measure. Both measures combined provide the strongest signal that returns will be negative in the coming days.

E. Subsample Analyses

To test the robustness of these patterns, we conduct a battery of robustness tests in Table XII. Because Robinhood users can trade with limited capital, low priced stocks are appealing to them, and thus we include such stocks in our analysis. One may be concerned that our results are driven by a tendency to observe closing prices at bid prices on the day of the herding event and thus on average negative returns the next day. The fact that most of the losses are observed during the next day (rather than overnight) suggests that bid-ask bounce is *not* the main driver of the results. To further address this issue, we reestimate the results using returns based on quote midpoints and find qualitatively similar results (Panel B). We also find reliably negative returns for stocks with prices in excess of \$5, but the return magnitudes are smaller (Panel C).

We anticipate that the negative returns we document will be present in small cap stocks but muted or nonexistent in large cap stocks, where retail trading is less likely to influence pricing. Consistent with this idea, we find that stocks

Table XII

Subsample of Postherding Return Patterns

The table presents the five-day abnormal return (%) from specifications (1) to (3) of Table X for various subsamples. Robust standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

	(1)	(2)	(3)
Panel A: Full Sample			
Five-day AR (%)	-2.942^{***}	-2.595^{***}	-2.630^{***}
Std. Err.	(0.322)	(0.350)	(0.348)
Panel B: Quote Midpoint Returns			
Five-day AR	-2.797^{***}	-2.378^{***}	-2.408^{***}
Std. Err.	(0.322)	(0.357)	(0.354)
Panel C: Only Stock with Prices > $5			
Five-day AR	-0.851^{***}	-0.756^{***}	-0.749^{**}
Std. Err.	(0.242)	(0.266)	(0.265)
Panel D: Small Cap (< $1 billion in Market Cap)			
Five-day AR	-4.250^{***}	-3.766^{***}	-3.835^{***}
Std. Err.	(0.418)	(0.434)	(0.432)
Panel E: Large Cap (> $1 billion in Market Cap)			
Five-day AR	0.14	−0.0348	−0.0508
Std. Err.	(0.534)	(0.517)	(0.521)
Panel F: Other than Common Stocks			
Five-day AR	-3.174^{***}	-2.895^{***}	-2.940^{***}
Std. Err.	(0.583)	(0.669)	(0.667)
Panel G: Post-Covid (after March 13, 2020)			
Five-day AR	-4.581^{***}	-2.876^{***}	-3.073^{***}
Std. Err.	(0.680)	(0.750)	(0.743)
Panel H: Pre-Covid (before March 13, 2020)			
Five-day AR	-2.221^{***}	-2.239^{***}	-2.231^{***}
Std. Err.	(0.337)	(0.327)	(0.330)

with a market cap less than $1 billion generate larger abnormal returns (−3.8 to −4.3%), while larger stocks with more than $1 billion in market cap have no discernable return pattern (Panels D and E). Our main results include both stocks and other securities (e.g., ADRs and exchange traded funds [ETFs]). We observe similar return patterns for these other securities only (Panel F).

We note that there was a large increase in both retail trading and Robinhood user holdings during the pandemic period (after March 13, 2020). We thus anticipate that the magnitude of the attention-induced subsequent poor performance will increase during this period. This is precisely what we observe (Panels G and H).

F. Sales Herding

As noted previously, attention asymmetrically affects buying and selling because investors can buy any stock but tend to sell only that which they own. Thus, driven by this theory of attention, our primary analysis focuses on the buying behavior of Robinhood investors. It is natural to wonder whether detectable return effects arise when we analyze sales herding events. To shed light on this question, we construct a sales herding variable that is analogous to our purchase herding variable. Specifically, we identify the securities in the bottom 0.5% of negative user changes as a percent of prior-day user count to construct the indicator variable *rh_negherd*.

It is worth noting that these sales herding events have user changes that are much less dramatic than the purchase herding events. For the nearly 4,900 sales herding events, the mean *userratio* is 0.87 and the median is 0.90 (see Table IAIX). Consistent with the attention model, the sales herding is less dramatic than the purchase herding. It is also worth noting that the sales herding events tend to follow purchase herding events and are more clustered than purchase herding events. For example, in a linear probability estimation that regresses the sales herding variable (*rh_negherd*) on lags of itself and lags of the purchase herding variable (*rh_herd*), the coefficients on lagged *rh_herd* are all significant and economically large—at one- and two-day lags, the coefficients are 0.192 and 0.132 (see Table IAX), orders of magnitude larger than the baseline probability of 0.0012. Roughly half of the sales herding events are preceded by a purchase herding event in the prior five days.

We next analyze the returns on the sales herding stocks using the regression format of Table X. We find that the sales herding events have relatively modest negative abnormal returns of about 55 to 63 bps over the five days following the decrease in users (see Table IAXI), and most of the negative abnormal returns follow sales herding events that occur after negative overnight returns (columns (6) to (9)). The return effects following sales herding events suggest that sales herding events are not as likely to create price pressure as purchase herding events, but rather accelerate the poor performance that follows purchase herding events.

G. Aggregate Investor Experience: Average Purchase and Sales Price

While we have found that herding events predict negative returns going forward, it could be the case that the Robinhood community still profits around these episodes. Enough investors could purchase the stock before the herding event for those users' profits to exceed any losses by later purchasers. To address this question, we compare the average purchase and sales prices for all users. Specifically, we compute the purchase prices of Robinhood users during the event period, $\tau = -10, +20$. Define $u_{i\tau} - u_{i,\tau-1} = \Delta u_{i\tau}$ as the change in users for stock i on event day τ. For event j, we calculate the average purchase price for days when we observe user increases ($\Delta u_{it} > 0$) as

$$PPrc_j = \frac{u_{i,-11}P_{i,-11} + \sum_{\tau=-10}^{+20} \mathrm{UI}_{i\tau}\,\Delta u_{i\tau} P_{i\tau}}{u_{i,-11} + \sum_{\tau=-10}^{+20} \mathrm{UI}_{i\tau}\,\Delta u_{i\tau}}. \quad (9)$$

The indicator $UI_{i\tau}$ equals one on days when the change in users is positive, $\Delta u_{i\tau} > 0$. Note that all users owning stock i at the close on day -11, before the event period begins, are assumed to have purchased at the closing price on day -11, that is, $P_{i,-11}$.

We next compute the average sales price on days when we observe a decrease in users. For any shares that are not sold during the event period, we assume that they are sold at the end of the event window:

$$SPrc_j = \frac{u_{i,20}P_{i,20} + \sum_{\tau=-10}^{+19} (1 - \mathrm{UI}_{i\tau})\,\Delta u_{i\tau} P_{i\tau}}{u_{i,20} + \sum_{\tau=-10}^{+19} (1 - \mathrm{UI}_{i\tau})\,\Delta u_{i\tau}}. \quad (10)$$

The profitability of event j is then calculated as the ratio of the sales price and the purchase price:

$$PrcRatio_j = \frac{SPrc_j}{PPrc_j} - 1. \quad (11)$$

The variable $PrcRatio_j$ represents the returns earned by the Robinhood community on event j.

In addition to computing raw returns, we compute returns that adjust for market movements. For each day during the event, we consider a counterfactual in which the Robinhood community buys or sells the equivalent amount of capital in an S&P 500 ETF, specifically, SPY. This provides us with a market price ratio ($MktPrcRatio_j$) for each stock event that we can use to benchmark the price ratio for the event stock. We report results in Figure 8.

On average, using raw returns, we find that the Robinhood community loses approximately 4.3% during each herding event. After adjusting for the market return, losses are about 5.5%. Both results are highly significant both statistically and economically. There are slight differences between the pre-COVID-19 and COVID-19 periods, although both suggest similar outcomes. Overall, these findings suggest that extreme herding causes negative wealth outcomes for the overall Robinhood community.[35]

IV. Short Trading and Herding Events

In the prior section, we find that Robinhood users' herding can lead to price pressure on the targeted stocks and subsequent poor performance. Our test

[35] In Figure IA6, we show that in the average event, about 60% of investors who buy during these herding episodes buy at a price that is higher than the observed price 20 days after the herding event. Sellers fare better, but buyers outnumber sellers by approximately 18.7 to 3.5 million.

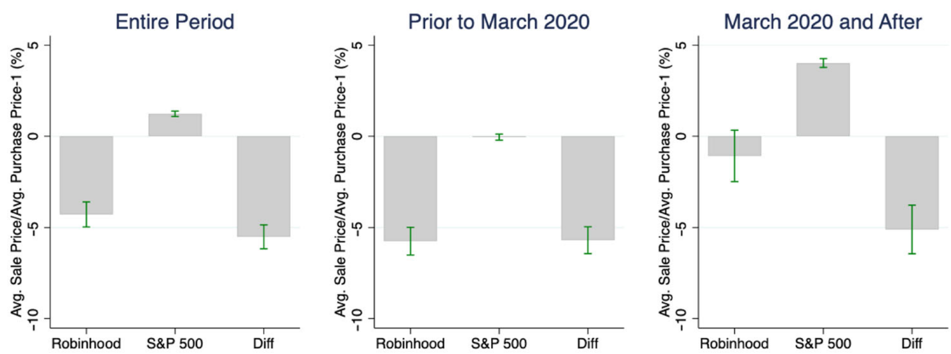

Figure 8. Aggregate investor experience: Average profitability. The figure presents the average profitability of the Robinhood user community's actual trades across the herding episodes, their counterfactual trades on S&P 500 ETF during the herding episodes, and the difference between the two. For each herding episode, we compute the weighted average purchase (sales) price of Robinhood users during the event period [−10,20]. Profitability is calculated as (average sales price/average purchase price − 1). Positive profitability indicates that the Robinhood community profited from that herding episode. The counterfactual trades on S&P 500 ETF assume that the Robinhood community purchases or sells the equivalent amount of capital in an S&P 500 ETF. The error bar represents the 95% confidence interval for the average. (Color figure can be viewed at wileyonlinelibrary.com)

design uses data available before the market closes, and therefore implies that the negative returns are tradable. In other words, other market participants could trade against Robinhood users' order flow in these herding situations in an attempt to profit from Robinhood users' correlated trading. In some sense, the disclosure of the stock holdings by Robinhood is similar to the disclosure of positions by mutual funds, hedge funds, and others through Form 13F. Hedge funds have argued that these disclosures enable other market participants to profit from their private information and to front-run their positions.[36] Researchers have documented that these disclosures are used by other market participants (e.g., Brown and Schwarz (2020)). Thus, it is somewhat surprising that Robinhood would voluntarily make holdings data available to other market participants who might profit from the data at the expense of Robinhood users.[37]

In this section, we evaluate whether other market participants do attempt to profit from the predictably negative returns that follow Robinhood herding

[36] It is not clear whether hedge fund 13Fs contain private information. Griffin and Xu (2009) find that 13F disclosures have no alpha as of their effective date. Brown and Schwarz (2020) find no alpha as of the date filed with the Security and Exchange Commission's EDGAR. Aiken, Clifford, and Ellis (2013) find that, after controlling for biases, hedge fund returns themselves have little alpha.

[37] Robinhood ceased releasing user data in August 2020, stating that the way the data are sometimes reported by third parties "could be misconstrued or misunderstood" and does not represent the company's user base (see https://www.foxbusiness.com/markets/robinhood-to-stop-sharing-of-apps-popular-stocks).

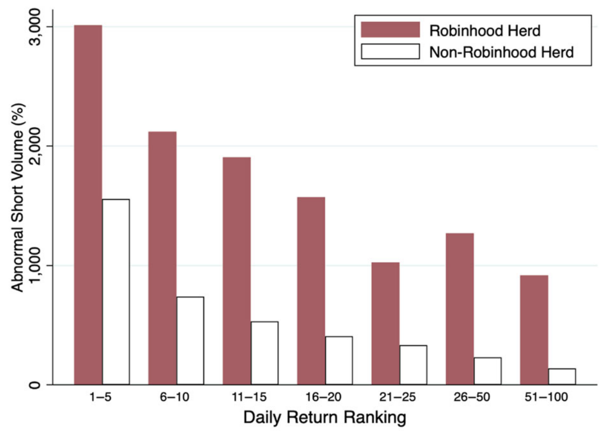

Figure 9. Short interest changes and Robinhood trading. The figure depicts average abnormal short trading (%). Short trading is measured using data from FINRA, which provides daily short trade data as noted by Boehmer and Song (2020). We measure abnormal short volume on day t as the ratio of short trades on day t to the prior 20-day ($[t-20, t-1]$) average of the number of short trades. To control for outliers, we winsorize the top 0.1% of observations. The x-axis is daily return ranking of day t. Robinhood Herd are the top 0.5% of stocks with a positive user change ratio on day t and a minimum of 100 users on day $t-1$. (Color figure can be viewed at wileyonlinelibrary.com)

events. To do so, we collect data from FINRA, which provides daily off-exchange short trade data as noted by Boehmer and Song (2020). Reed, Samadi, and Sokobin (2020) point out that off-exchange short sales are less informative than exchange short sales, so our use of off-exchange short data is expected to underestimate the actions of informed trades. We compute the abnormal short volume on herding day t as the ratio of the number of short trades on day t divided by the average number of short trades from days $t-20$ to $t-1$. We also winsorize the top 0.1% to control for extreme outliers.

To begin our analysis, we examine the relation between top stock performance, Robinhood herding, and short trading. Specifically, we calculate the daily return rank for each stock, as we expect abnormal short trading to be correlated with high returns. We then flag whether the stock was also herded into by Robinhood users any day during the period using our 0.5% cutoff (*rh_herd*). We calculate the average change in abnormal short volume for each return rank for the non-Robinhood herding and Robinhood herding groups separately. In Figure 9, we plot the average values for ranks 1–5, 6–10, 11–15, 16–20, 21–25, 26–50, and 51–100.

We find two clear patterns. First, abnormal short volume is indeed higher for stocks that had a high daily return rank. Second, in all cases abnormal short volume for stocks herded into by Robinhood investors is far higher than that for stocks not herded into Robinhood investors. This is consistent with market participants knowing the pattern of Robinhood return reverses and,

Table XIII
Regression of Abnormal Short Trading on Returns and Top Robinhood Changes

The dependent variable is abnormal short volume. Short volume is measured using data from FINRA, which provides daily short trade data as noted by Boehmer and Song (2020). We compute abnormal short volume on day t as the ratio of short trades on day t to the prior 20-day ($[t-20, t-1]$) average of the number of short trades. The top 0.1% of observations are winsorized. The key independent variables are *rh_chgratio*, which is the percentage change in users from day $t-1$ to t, and *rh_herd*, which is an indicator variable that equals one if the percentage change in users is in the top 0.5% for stocks with positive user changes on day t and a minimum of 100 users on day $t-1$. Control variables include the excess return of day t, dummy variables representing the return ranks (*ret_rank*) of day t, and abnormal news coverage, which is the logarithm of the ratio of news article count on day t to the average news article count from day $t-20$ to $t-1$. Coefficients are in percent. Standard errors are computed using Fama-Macbeth (1973). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	Abnormal Short Volume (%)			
	(1)	(2)	(3)	(4)
rh_chgratio	637.14***		551.10***	
	(12.75)		(11.10)	
rh_herd		854.65***		686.57***
		(14.5)		(17.25)
Excess return	499.54***	498.83***		
	(16.32)	(15.95)		
Abnormal News	6.64***	7.17***	6.37***	6.85***
	(0.13)	(0.14)	(0.12)	(0.13)
Ret_rank_1			858.14***	1049.44***
			(47.95)	(36.36)
Ret_rank_2			704.80***	818.70***
			(44.31)	(34.22)
Ret_rank_3			568.94***	670.82***
			(68.35)	(32.64)
Ret_rank_4			583.67***	635.83***
			(35.00)	(31.91)
Ret_rank_5			534.46***	554.07***
			(30.95)	(30.50)
Ret_rank_6			465.52***	480.40***
			(26.90)	(26.95)
Ret_rank_7			410.78***	482.44***
			(39.91)	(28.08)
Ret_rank_8			371.97***	398.30***
			(27.60)	(25.01)
Ret_rank_9			381.49***	395.11***
			(26.37)	(26.27)
Ret_rank_10			361.47***	385.87***
			(24.36)	(24.53)
Ret_rank_11 − 25			269.46***	279.53***
			(8.20)	(8.55)
Ret_rank_26 − 50			145.48***	152.75***
			(4.30)	(4.56)
Ret_rank_51 − 100			83.45***	86.87***
			(2.31)	(2.45)
Observations	2,681,173	2,681,173	2,681,173	2,681,173
Avg. R^2	0.162	0.146	0.271	0.257

more broadly, with market participants using the disclosed Robinhood position information.

We next examine short-interest changes in a multivariate setting. Each period, we regress abnormal short trading on either the daily excess return or the return ranking (*ret_rank*). We also include abnormal news coverage to control for attention that news may have brought and caused. Our primary variables of interest are either the average user change ratio during the period (*rh_chgratio*) or herding of the stock by Robinhood users (*rh_herd*). We average across periods and obtain standard errors and t-values via Fama and Macbeth (1973).

In Table XIII, we find results consistent with those of Figure 9. A 100% increase (doubling) in the average change ratio leads to at least a 637% increase in short trading (column (1)), which is both statistically and economically significant. If a stock is herded by Robinhood users (columns (2)), abnormal short volume is approximately 855% higher than if the stock is not herded. Overall, these results again suggest strongly that market participants examined Robinhood ownership data, knew about the subsequent poor performance caused by Robinhood herding, and traded against Robinhood order flow.

V. Conclusion

The stated mission of the Robinhood brokerage is to "democratize finance for all…[and] make investing friendly, approachable, and understandable." Robinhood facilitates "friendly, approachable, and understandable" investing by offering a simple downloadable app that makes trading incredibly easy. The app displays only a small fraction of the stock-level indicators that other brokerage platforms provide. Instead, the app highlights easily understood lists of stocks such as a Top Movers list of stocks with the largest price moves on the current day.

We argue that the combination of simplified information display and inexperience exacerbates attention-driven buying by Robinhood users. Heightened attention-driven buying leads to more concentrated trading by Robinhood users than other retail investors and contributes to buy-side herding events that are usually followed by negative returns. For example, the top 0.5% of stocks bought by Robinhood users each day experiences negative average returns of approximately 5% over the next month. More extreme herding events are followed by negative average returns of almost 20%.

Robinhood has been successful in its stated mission in as much as it has attracted 13 million users (as of 2020). Half of these are first-time investors, who are likely in the long run to benefit from participating in markets. Robinhood attracts investors by reducing frictions and promoting simplicity. While a lack of frictions encourages market participation, it also makes speculative trading easy, which can lead to lower investment returns (Odean (1999), Barber and Odean (2000), Barber et al. (2009)). However, even in an industry that uses complexity to obscure risks and costs (Carlin (2009), Henderson and Pearson (2011); Célérier and Vallée (2017), Gao et al. (2021)), simplicity is not problem free. As we show, simply focusing the attention of many investors on a small number of stocks can promote herding behavior that affects market returns and redounds to the investors' detriment. Thus, while it is important that investors have access to transparent, pertinent information, disclosure alone is not sufficient to assure good investor outcomes—how information is displayed influences decisions in ways that can both help and hurt investors.

Initial submission: February 2, 2021; Accepted: September 12, 2021
Editors: Stefan Nagel, Philip Bond, Amit Seru, and Wei Xiong

REFERENCES

Aiken, Adam L., Christopher P. Clifford, and Jesse Ellis. 2013, Out of the dark: Hedge fund reporting biases and commercial databases. *Review of Financial Studies* 26, 208–243.

Barber, Brad M., Yi-Tsung Lee, Yu-Jane Liu, and Terrance Odean. 2009, Just how much do individual investors lose by trading? *Review of Financial Studies* 22, 609–632.

Barber, Brad M., Shengle Lin, and Terrance Odean. 2021, Resolving a paradox: Retail trades positively predict returns but are not profitable, Working paper.

Barber, Brad M., and Douglas Loeffler. 1993, The "Dartboard" column: Second-hand information and price pressure. *Journal of Financial and Quantitative Analysis* 28, 273–284.

Barber, Brad M., and Terrance Odean. 2000, Trading is hazardous to your wealth: The common stock investment performance of individual investors, *Journal of Finance* 55, 773–806.

Barber, Brad M., and Terrance Odean. 2002, Online investors: Do the slow die first? *Review of Financial Studies* 15, 455–488.

Barber, Brad M., and Terrance Odean. 2008, All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. *Review of Financial Studies* 21, 785–818.

Barber, Brad M., Terrance Odean, and Ning Zhu. 2008, Do retail trades move markets? *Review of Financial Studies* 22, 151–186.

Boehmer, Ekkehart, Charles M. Jones, Xiaoyan Zhang, and Xinran Zhang. 2021, Tracking retail investor activity. *Journal of Finance* 76, 2249–2305.

Boehmer, Ekkehart, and Wanshan Song. 2020, Smart retail traders, short sellers, and stock returns, Working paper.

Bolster, Paul, Emery Trahan, and Anand Venkateswaran. 2012, How mad is mad money? Jim Cramer as a stock picker and portfolio manager. *Journal of Investing* 21, 27–39.

Brown, Stephen J., and Christopher Schwarz. 2020, Do market participants care about portfolio disclosure? Evidence from hedge funds' 13F filings, Working paper.

Campbell, John Y., Sanford J. Grossman, and Jiang Wang. 1993, Trading volume and serial correlation in stock returns. *Quarterly Journal of Economics* 108, 905–939.

Carlin, Bruce I. 2009, Strategic price complexity in retail financial markets. *Journal of Financial Economics* 91, 278–287.

Célérier, Claire, and Boris Vallée. 2017, Catering to investors through security design: Headline rate and complexity. *Quarterly Journal of Economics* 132, 1469–1508.

Cheng, Peter, Thomas J. Murphy, and Marko Kolanovic. 2020, Following the robinhood money. JP Morgan report.

Choi, James J., David Laibson, and Brigitte C. Madrian. 2010, Why does the law of one price fail? An experiment on index mutual funds. *Review of Financial Studies* 23, 1405–1432.

Cookson, J. Anthony, Joseph Engelberg, and William Mullins, Forthcoming, Echo chambers. *Review of Financial Studies*.

Coval, Joshua, and Erik Stafford. 2007, Asset fire sales (and purchases) in equity markets. *Journal of Financial Economics* 86, 479–512.

Cronqvist, Henrik, and Richard H. Thaler. 2004, Design choices in privatized social-security systems: Learning from the Swedish experience. *American Economic Review* 94, 424–428.

Da, Zhi, Joseph Engelberg, and Pengjie Gao. 2011, In search of attention. *Journal of Finance* 66, 1461–1499.

Da, Zhi, Jian Hua, Chih-Ching Hung, and Lin Peng, 2020, Market returns and a tale of two types of attention, Working paper.

Da, Zhi, Borja Larrain, Clemens Sialm, and Jose Tessada. 2018, Destabilizing financial advice: Evidence from pension fund reallocations. *Review of Financial Studies* 31, 3720–3755.

Drechsler, Itamar, Alan Moreira, and Alexi Savov. 2020, Liquidity and volatility, Working paper.

Eaton, Gregory W., Clifton Green, Brian Roseman, and Yanbin Wu, Forthcoming, Retail trader sophistication and stock market quality: evidence from brokerage outages. *Journal of Financial Economics*.

Engelberg, Joseph, Caroline Sasseville, and Jared Williams. 2012, Market madness? The case of mad money. *Management Science* 58, 351–364.

Fama, Eugene F., and James D. MacBeth. 1973, Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy* 81, 607–636.

Fedyk, Anastassia. 2019, Front page news: The effect of news positioning on financial markets, Working paper.

French, Kenneth R., and Richard Roll. 1986, Stock return variances: The arrival of information and the reaction of traders. *Journal of Financial Economics* 17, 5–26.

Frydman, Cary, and Baolian Wang. 2020, The impact of salience on investor behavior: Evidence from a natural experiment. *Journal of Finance* 75, 229–276.

Gao, Pengjie, Allen Hu, Peter Kelly, and Cameron Peng. 2021, Exploited by complexity, Working paper.

Greenwood, Robin, and Stefan Nagel. 2009, Inexperienced investors and bubbles. *Journal of Financial Economics* 93, 239–258.

Griffin, John M., and Jin Xu. 2009, How smart are the smart guys? A unique view from hedge fund stock holdings. *Review of Financial Studies* 22, 2331–2370.

Henderson, Brian J., and Neil D. Pearson. 2011, The dark side of financial innovation: A case study of the pricing of a retail financial product. *Journal of Financial Economics* 100, 227–247.

Hong, Claire Yurong, Xiaomeng Lu, and Jun Pan. 2019, FinTech platforms and mutual fund distribution, Working paper.

Jegadeesh, Narasimhan. 1990, Evidence of predictable behavior of security returns. *Journal of Finance* 45, 881–898.

Jegadeesh, Narasimhan, and Sheridan Titman. 1995, Overreaction, delayed reaction, and contrarian profits. *Review of Financial Studies* 8, 973–993.

Kaniel, Ron, and Robert Parham. 2017, WSJ category kings–the impact of media attention on consumer and mutual fund investment decisions. *Journal of Financial Economics* 123, 337–356.

Kaniel, Ron, Gideon Saar, and Sheridan Titman. 2008, Individual investor trading and stock returns. *Journal of Finance* 63, 273–310.

Kahneman, Daniel. 1973, Attention and Effort (Prentice-Hall, Englewood Cliffs, NJ).

Kahneman, Daniel. 2011, Thinking, Fast and Slow (Farrar, Straus and Giroux, NY).

Keasler, Terrill R., and Chris R. McNeil. 2010, Mad money stock recommendations: Market reaction and performance. *Journal of Economics and Finance* 34, 1–22.

Kelley, Eric K., and Paul C. Tetlock. 2013, How wise are crowds? Insights from retail orders and stock returns. *Journal of Finance* 68, 1229–1265.

Kronlund, Mathias, Veronika K. Pool, Clemens Sialm, and Irina Stefanescu. 2021, Out of sight no more? The effect of fee disclosures on 401(k) investment allocations. *Journal of Financial Economics* 141, 644–668.

Lakonishok, Josef, Andrei Shleifer, and Robert W. Vishny. 1992, The impact of institutional trading on stock prices. *Journal of Financial Economics* 32, 23–43.

Liang, Bing. 1999, Price pressure: Evidence from the "Dartboard" column. *Journal of Business* 72, 119–134.

Lehmann, Bruce N. 1990, Fads, martingales, and market efficiency. *Quarterly Journal of Economics* 105, 1–28.

Lo, Andrew W., and A. Craig MacKinlay. 1988, Stock market prices do not follow random walks: Evidence from a simple specification test. *Review of Financial Studies* 1, 41–66.

Lo, Andrew. W., and A. Craig MacKinlay. 1990, When are contrarian profits due to stock market overreaction? *Review of Financial Studies* 3(2), 175–205.

Loos, Benjamin, Steffen Meyer, and Michaela Pagel. 2020, The consumption effects of the disposition to sell winners and hold losers, Working paper.

Nagel, Stefan. 2012, Evaporating liquidity. *Review of Financial Studies* 25, 2005–2039.

Niessner, Marina. 2015, Strategic disclosure timing and insider trading, Working paper.

Odean, Terrance. 1999, Do investors trade too much? *American Economic Review* 89, 1279–1298.

Oprea, Ryan. 2020, What makes a rule complex? *American Economic Review* 110, 3913–3951.

Ozik, Gideon, Ronnie Sadka, and Siyi Shen. 2021, Flattening the illiquidity curve: Retail trading during the COVID-19 lockdown. *Journal of Financial and Quantitative Analysis* 56, 2356–2388.

Pedersen, Lasse H., Forthcoming, Game on: Social networks and markets. *Journal of Financial Economics*.

Reed, Adam V., Mehrdad Samadi, and Jonathan S. Sokobin. 2020, Shorting in broad daylight: Short sales and venue choice. *Journal of Financial and Quantitative Analysis* 55, 2246–2269.

Seasholes, Mark S., and Guojun Wu. 2007, Predictable behavior, profits, and attention. *Journal of Empirical Finance* 14, 590–610.

So, Eric C., and Sean Wang. 2014, News-driven return reversals: Liquidity provision ahead of earnings announcements. *Journal of Financial Economics* 114, 20–35.

Tetlock, Paul C. 2011, All the news that's fit to reprint: Do investors react to stale information? *Review of Financial Studies* 24, 1481–1512.

Umar, Tarik. 2020, Complexity aversion when seeking alpha, Working paper.

Vissing-Jørgensen, Annette. 2002, Limited asset market participation and the elasticity of intertemporal substitution. *Journal of Political Economy* 110, 825–853.

Welch, Ivo. 2022, Retail raw: Wisdom of the Robinhood crowd and the covid crisis. *Journal of Finance* 77, 1489–1527.

Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Appendix S1: Internet Appendix.
Replication Code.