Fast and Furious: A High-Frequency Analysis of Robinhood Users' Trading Behavior*

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Abstract

We study Robinhood (RH) investors' trading behavior in response to intraday and overnight price changes. We find that RH users tend to open new positions in stocks that experience large negative intraday and overnight price movements. They also demonstrate asymmetric behavior in response to extremely negative and positive returns, favoring intraday or overnight losers over gainers. Their response to large negative price movements is particularly rapid. These behaviors are more pronounced following overnight returns in comparison to intraday returns, and are exacerbated during the post-COVID-19 period, for larger-cap stocks, and energy and consumer discretionary stocks.

Keywords: Retail investors, Robinhood, Overnight Returns, Intraday Returns, COVID-19, FinTech
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1. Introduction

Retail participation in the stock market has risen significantly in recent years, with individual investors accounting for over 40% of total trades in Q1 2021 in the United States.[1] This trend is attributed to the rise of new FinTech, commission-free trading platforms such as Robinhood Market Inc., whose user base has grown rapidly, reaching 22.5 million by the end of 2021. Robinhood (hereafter RH), with its mission to "democratize finance for all," aims to make investing more accessible. It has attracted a new demographic of young and inexperienced investors who trade small amounts.[2] Most of these new investors belong to the "millennials" generation and have always been immersed in the modern digital society. They trade almost exclusively via the RH smartphone application, and are heavy consumers of social media. Besides, they have been known to create significant stock price movements (*e.g.*, the "Hertz bankruptcy saga" in mid-2020 or the "GameStop episode" in early 2021) and contribute to increased market volatility.[3]

As the emergence of this new type of investor poses challenges for regulators (see *e.g.*, Fisch, 2022) and market participants, it is not surprising to find a growing body of literature analyzing their trading behavior. For example, Barber et al. (2022) demonstrate that some features of the RH smartphone app can heavily influence the way RH investors trade, and Welch (2022) analyses the performance and composition of a representative RH investors' portfolio. These studies, and many others, provide key results at the daily frequency. However, little is known about RH traders' behavior during the day. Yet, given their ultra-connected and tech-savvy specificity, it is likely that RH investors are active throughout the day. The RH smartphone app can send them real-time notifications and triggers a buy or sell decision. Furthermore, compared to traditional retail investors, millennials have easier and faster access to information. This allows them to react faster to new information, making it crucial to examine their behavior at a higher frequency.[4]

In this paper, we fill this gap by investigating the trading behavior of RH investors using hourly intraday and overnight observations. More specifically, we examine how RH investors trade in response to intraday and overnight stock price changes. We focus on previous stock price movements because these young and inexperienced investors are likely to "trade on noise" (Black, 1986) and to be particularly influenced by attention-grabbing events (see *e.g.*,

[1] See The Economist [url].

[2] The average age of its users is only 31, and about 50 percent are first-time investors. Their average account size is only $4,000, compared to $127,000 or $234,000 for major competitors E-Trade and Charles Schwab, respectively. The profile of the RH investor has been extensively discussed in the press (see *e.g.*, NextAdvisor [url], New York Times [url], Business*of*Apps [url], CNN Business [url], CNBC Markets [url1, url2], Forbes Advisor [url], Barron's [url], Robinhood's blog [url]) and drawn multiple times in scientific papers (see *e.g.*, Barber et al., 2022; Welch, 2022; Eaton et al., 2022; Van der Beck and Jaunin, 2021; Jones et al., 2021).

[3] For more details on the Hertz and GameStop events, see Forbes Advisor [url] (Hertz) and CNBC Markets [url] (GameStop). For the impact of Robinhood users on volatility, see *e.g.*, Aharon et al. (2022).

[4] A recent study shows that new active retail investors adopt "a significantly higher trading frequency, but on smaller orders than those found for the clients of the other categories of intermediaries" (see AMF Report, 2021).

Barber and Odean, 2008; Seasholes and Wu, 2007). Given this proclivity, they should pay special attention to the simplest market events, or those prominently displayed on their smartphone screens: previous returns.[5] Additionally, using a deeper level of granularity can provide insights that would not be possible to obtain using lower-frequency scales. In particular, we explore new questions, such as evaluating RH investors' speed of response to extreme price movements and the differentiation of their trading behavior based on overnight versus intraday returns.

We conduct our analyses using data on RH investors' holdings from Robintrack.net and high-frequency transaction prices from the NYSE Daily Trade And Quote product. Our panel dataset includes over 2,500 stocks and covers the period from June 1, 2018, to August 13, 2020, with more than seven million entries of hourly intraday and overnight observations. We use a regression framework to study the relationship between RH investors' trading behavior and previous stock returns. The dependent variable is a proxy for their behavior, and the regressors are lagged volatility-adjusted intraday and overnight stock returns, grouped into percentile ranges. This allows us to capture the propensity of RH investors to buy new stocks after observing previous intraday and overnight price movements of different signs and magnitudes.

Our analyses identify three key behaviors among RH investors. First, we observe that shortly after observing a sharp decline in a stock's price, RH investors tend to add this stock to their portfolios. Second, RH investors behave asymmetrically with respect to extreme movements, favoring stocks with large negative returns (the "big losers") over stocks with large positive returns (the "big winners"). Put differently, they open more new positions in sharply declining stocks compared to sharply rising stocks. Third, we find that they respond particularly quickly to large negative movements: they open new positions in stocks with extremely negative returns in the first hour following such movements, while there are fewer position openings beyond one hour. This high speed of response is specific to large negative movements and not observed for moderate or large positive returns. The common point between these three behaviors is that they are all linked to large negative movements. For other types of movements (*e.g.*, moderate returns, large positive returns), we cannot identify clear patterns. Thus, RH investors seem particularly focused on these large negative intraday and overnight movements.

Next, we examine these three behaviors under various conditions. We begin by differentiating the response to overnight and intraday price movements. For instance, regarding the

[5] While other factors may also play a role in the decision-making process of RH investors, such as the company's long-term prospects, liquidity, etc., we believe that these are of secondary importance to the RH community. As previously mentioned, social media is another important source of information for individual traders, and this has been the subject of many studies (see *e.g.*, Bollen and Zeng, 2011; Grennan and Michaely, 2020; Hsieh et al., 2020; Hao and Xiong, 2021; Hu et al., 2021; Farrell et al., 2022; Liaukonytė and Žaldokas, 2022; Meshcheryakov and Winters, 2022; Pedersen, 2022). This channel can play a major role in specific events, such as the Reddit forum *r/wallstreetbets* in the GameStop saga. In this paper, however, we do not focus on such specific events. Instead, relying on a large universe of over 2,500 stocks and a period of more than 500 trading days, we seek to identify trading behaviors in a more general framework.

first behavior, the tendency to open new positions in stocks that experience large negative movements, we investigate whether RH investors open more or fewer new positions if the movement occurs overnight or during trading hours. We also consider whether RH investors exhibit more or less asymmetry in response to extreme returns depending on whether the extreme returns occur at night or during the day (second behavior). Additionally, we examine whether RH investors respond more or less quickly to large negative returns that occur overnight or during the day (third behavior). This research complements existing studies that distinguish between overnight and intraday returns. For example, Lou et al. (2019) argue that there exists an "overnight clientele" and an "intraday clientele"; Jones et al. (2022) examine morning order imbalances in relation to previous daytime ("close to open") and overnight returns; and Berkman et al. (2012) show that "high-attention stocks have high levels of net retail buying at the start of the trading day." We find that all three behaviors are more pronounced for overnight returns. The inclination of RH investors to open more new positions in stocks that exhibit large negative returns is approximately seven times larger when this large movement occurs overnight as opposed to during trading hours. The asymmetry of response is stronger after an overnight return as compared to an intraday return, indicating that RH investors tend to open more new positions in overnight losers relative to overnight winners, in comparison to intraday losers relative to intraday winners. Regarding the third behavior, the speed of response to large negative movements, RH investors are faster to react to overnight versus intraday returns.

Then, we focus on the effect of the COVID-19 pandemic on these trading behaviors. As most of the population was confined, with limited access to social or sporting activities, many young people were spurred to start investing at that time.[6] Consistent with the findings of Ozik et al. (2021), we observe that RH investors' buying activity has largely increased in the post-COVID-19 period. Also, post-COVID-19, RH investors have been opening more new positions in falling stocks (first behavior) and responding more quickly to stocks experiencing large downward movements (third behavior).

We also analyze the relationship between company size and RH investors' trading behaviors. We find that the behaviors are more pronounced for large-cap stocks. Specifically, RH investors open more new positions in large-cap stocks with very negative returns in comparison to smaller stocks. They also exhibit a stronger asymmetry in response to extreme returns of large-cap stocks, and respond more quickly to large negative returns for large-cap stocks. These findings tend to contrast with previous research that has demonstrated that individual investors exhibit stronger herding behavior for small stocks (see *e.g.*, Venezia et al., 2011; Hsieh et al., 2020) and have a comparative advantage in trading small-cap stocks (see *e.g.*, Kelley and Tetlock, 2013; Jirajaroenying et al., 2019).[7] However, when specifically examining the behavior of RH investors, Welch (2022) has shown that, on aggregate, they

[6] See CNBC Markets [url].

[7] As Kumar and Lee (2006) and Kumar (2009) show, retail investors also tend to be more attracted by small-*price* stocks. In general, there is a high degree of overlap between small-price and small-cap stocks.

actually hold more large-cap than small-cap stocks.

Finally, we examine how these behaviors vary by industry and find that the Energy and Consumer Discretionary sectors exhibit stronger behaviors. Specifically, RH investors tend to open more new positions in stocks in these sectors following large negative price movements; they exhibit a stronger asymmetry in their response to extreme returns for Consumer Discretionary stocks; and they respond more quickly to sharply declining Energy stocks.

Our research is part of the vast literature studying retail investors, dating back to the seminal article by Black (1986) who demonstrated that individual investors are noise traders and uninformed, as several studies have confirmed more recently (see, *e.g.*, Kumar and Lee, 2006; Foucault et al., 2011; Fong et al., 2014). More specifically, we contribute to the body of literature that focuses on retail investors' attention.[8] Our study has strong links to the work of Barber and Odean (2008), who investigate the impact of news from DJ News Service, unusual volume, and past extreme returns on individuals' trading decisions using data from brokerage accounts. Among the results of particular interest to us, they find that retail investors tend to buy stocks posting extreme returns (both negative and positive) the previous day.[9] Our study differs in at least three ways. First, we investigate the behavior of a new type of investor: RH investors. Second, unlike their study which concentrates on daily behavior, we focus on their behavior during the day and night. As mentioned before, we believe that the difference in frequency is highly important given the millennial profile of RH investors. Third, we address new questions, particularly about the speed of response to previous price movements and the differentiation of their attitudes towards overnight and intraday returns.

We also contribute to the rapidly-expanding literature on RH investors, particularly relating to two studies: Barber et al. (2022) and Welch (2022). Among their key results, Barber et al. (2022) demonstrate that the unique features of the RH smartphone app influence how RH investors trade. Specifically, they show that the "top movers" feature of the app, which does not differentiate between losers and gainers, leads to a more symmetrical behavior in relation to extreme returns among RH investors compared to other retail investors. In contrast, using a higher frequency framework and a larger universe of stocks, our study observes that RH investors exhibit an asymmetric buying behavior with respect to extreme returns (in favor of losers). Combined, our findings and those of Barber et al. (2022) complement each other. On the one hand, our observation that the symmetry identified in Barber et al. (2022) does not hold for a larger universe of stocks tends to support that this top movers

[8]In contrast to a major strand of this literature that focuses on individual investors' performance or asset pricing implications (see, *e.g.*, Barber et al., 2009a; Hvidkjaer, 2008; Kaniel et al., 2008; Barber et al., 2009b; Kelley and Tetlock, 2013; Gargano and Rossi, 2018; Coval et al., 2021; de Silva et al., 2022; Lehnert, 2022), we are not interested into whether RH investors make profits. Instead, we focus on the choices that drive this performance, that is, their decision-making process to buy or sell a certain stock.

[9]A comparable study is conducted by Yuan (2015). He uses extreme returns of the DJIA and news from the New York Times and Los Angeles Times to proxy for attention, and all orders below a certain size to proxy for investors' trading behavior.

feature does influence the behavior of RH investors. On the other hand, our results also indicate that the attitude of RH investors towards extreme movers may vary depending on the frequency at which their behavior is assessed, with different patterns emerging at different levels (intraday and overnight versus day-to-day). In a second important paper for our study, Welch (2022) constructs a representative RH investor portfolio and analyzes its composition and performance. Using a larger universe of stocks than Barber et al. (2022), he also demonstrates that RH investors tend to buy both the big winners and the big losers at a daily frequency. Interestingly, he finds that "this effect is weaker for large stock price decreases than for large stock price increases", that is, there is an asymmetry in favor of large *gainers*. Our study confirms this attraction-to-extreme-movers behavior but demonstrates that, in a higher frequency setting, the asymmetry shifts in favor of large losers. Additionally, we contribute new empirical findings related to RH investors' speed of response to previous extreme returns, the differentiation between overnight and intraday movements, and the decomposition of behavior by stock size and industry.[10]

The rest of the paper is organized as follows. Section 2 presents the data and introduces our main variables. Section 3 presents the methodology and all empirical results. Section 4 concludes.

2. Data and Variable Definitions

2.1. Robinhood Users' Holdings and High-Frequency Prices

Between 2018 and 2020, Robintrack.net utilized Robinhood's API to collect data on the number of investors holding a specific stock at a specific time (*e.g.*, 300,000 RH users hold AMZN on 2018-06-04 at 10:45 a.m.), and then shared this information through the website. Following Barber et al. (2022) or Welch (2022), we use this data from Robintrack to proxy for RH investors' trading behavior. Unlike these studies, however, we consider intraday and overnight observations rather than daily observations. Specifically, we denote by $N_{i,t_{i,k}}$ the number of RH investors holding security i at time $t_{i,k}$, where k is an index indicating the kth observation for stock i.

The original time provided by Robintrack denotes the time at which the information was retrieved from Robinhood.com. However, as confirmed by our discussions with the

[10] Although less closely related to our study, several papers attempt to exploit periods of outages in the RH platform (periods where RH investors cannot trade due to technical breakdowns) to examine the effect RH investors might have on the market. For example, Eaton et al. (2022) find that during RH outages, market liquidity of RH-favored stocks improves, and their volatility decreases. Friedman and Zeng (2021) demonstrated that during these outages, retail activity is reduced and bid-ask spreads narrow. In the same spirit, Jones et al. (2021) exploit trade restrictions imposed by retail-oriented brokerage firms, including Robinhood, and show that these restrictions substantially affect stock prices. Other important references include Moss et al. (2020) who find that RH investors did not particularly care about ESG investing; Ozik et al. (2021) who show that during the COVID-19 pandemic lockdown in Spring 2020, RH investors' activity sharply increased as investors were able to trade from home; Ben-David et al. (2022) who find that "sentiment-driven investors" like RH investors are particularly prone to invest in thematic ETFs; and Van der Beck and Jaunin (2021) who develop a structural model to quantify the impact of Robinhood traders on the US equity market.

administrator of Robintrack, Casey Primovic, and indicated in Barber et al. (2022), there is an approximate 45-minute delay between the actual observation time and the time of retrieval. It implies that a data point with an original time of 10:45 a.m., for example, represents a snapshot of the data as of approximately 10:00 a.m. Therefore, to ensure accuracy and work with observation times, we subtract 45 minutes from all timestamps $t_{i,k}$.[11]

An increase in $N_{i,t_{i,k}}$ indicates that more RH users are opening new positions in (*i.e.*, acquiring) stock i, relative to those who are liquidating their existing positions. While this metric does not reveal the exact number of shares held by each account and, as noted in Welch (2022), can be affected by Robinhood's referral program that offers free shares to new investors, it provides valuable insight into RH users' demand for a given stock.

Our other main data are the transaction prices up to the millisecond frequency obtained from the NYSE Daily Trade And Quote databases. We match all RH users' holdings observations ($N_{i,t_{i,k}}$) to the last trade price available of stock i before time $t_{i,k}$. For each stock, we also match the $N_{i,t_{i,k}}$ observations to the last trade price available of the SPDR S&P 500 ETF (SPY), our market proxy, before time $t_{i,k}$. To minimize the effect of micro-structure issues on our results, we apply filters during our extraction process based on the procedure of Barndorff-Nielsen et al. (2009). In particular, we retain entries originating from the three main exchanges: NYSE, NASDAQ, and AMEX.

The original database from Robintrack comprises over 140 million observations that are approximately one-hour spaced, on more than 8,000 distinct securities. To ensure data quality, we apply several adjustments. In particular, we follow Welch (2022) and drop the first month of the original period. To match RH users' holdings and trade prices, we focus on observations made during market-opening hours (9:30 a.m.–4:00 p.m.). We also only retain common-stocks type securities (CRSP share codes of 10 or 11). We identify and remove dual-class tickers that were not properly named, and adjust for repeated intra-hour observations. A detailed list of our adjustments is provided in the Internet Appendix. After all adjustments, our final sample contains over 7.5 million observations on 2,585 stocks and 527 trading days from June 1, 2018 to August 13, 2020.

2.2. Variable Definitions

Our primary variable of interest is the change in the number of RH users holding a given stock between two consecutive observations. This variable, to which we will refer as the "net position openings" indicator, serves as a proxy for the aggregate trading behavior of RH users with respect to a given stock. We define it as

[11] We can provide results based on 30-minute or 60-minute delays upon request, as the actual delay may vary within that range.

$$\Delta N_{i,t_{i,k}} = \begin{cases} \log\left(\frac{N_{i,t_{i,k}}}{N_{i,t_{i,k-1}}}\right) \times SF_{INT} & \text{for an intraday change} \\ \log\left(\frac{N_{i,t_{i,k}}}{N_{i,t_{i,k-1}}}\right) \times SF_{OV} & \text{for an overnight change} \end{cases}. \tag{1}$$

An intraday change is approximately a one-hour change between two observations of $N_{i,t_{i,k}}$ of the same day. An overnight change corresponds to a change between the last observation of $N_{i,t_{i,k}}$ before the closing time of a trading day and the first observation of $N_{i,t_{i,k}}$ after the opening time of the next trading day. For consistency and to facilitate comparisons between overnight and intraday returns, we convert these two types of change into daily units using the scaling factors SF_{INT} and SF_{OV}. We assume that a full-day is the addition of two (equally-weighted) parts, overnight and intraday. In the top equation, $SF_{INT} \equiv \frac{60}{MNT(t_{i,k-1},t_{i,k})} \times 6.5 \times 2$. The first term normalizes the change to an exactly one-hour period where $MNT(t_{i,k-1}, t_{i,k})$ is the number of minutes between the consecutive times $t_{i,k-1}$ and $t_{i,k}$. The second term converts this hourly change into a "total daytime" (from open to close time) change as the market is open during 6.5 hours. The last term converts this total daytime change into a full-day (*i.e.* overnight + daytime) change. Similarly, in the bottom equation, $SF_{OV} \equiv 2$ converts the overnight change into a full-day change.[12]

To compute intraday and overnight stock returns, we proceed similarly and define

$$R_{i,t_{i,k}} = \begin{cases} \log\left(\frac{p_{i,t_{i,k}}}{p_{i,t_{i,k-1}}}\right) \times SF_{INT} & \text{for an intraday return} \\ \log\left(\frac{p_{i,t_{i,k}}}{p_{i,t_{i,k-1}}}\right) \times SF_{OV} & \text{for an overnight return} \end{cases} \tag{2}$$

where $p_{i,t_{i,k}}$ is the price of stock i at time $t_{i,k}$. As above, we use the scaling factors SF_{INT} and SF_{OV} to convert the returns into daily units.

In our analyses, we will pay special attention to extreme movements. To capture them, we adjust the returns in (2) using a standardization procedure based on a daily volatility estimator. As advocated by Andersen et al. (2011) and, more recently Santos et al. (2022), we use a dedicated estimator to normalize the intraday and overnight returns separately. For intraday returns, we use a five-min ticks Subsampling Realized Volatility estimator as developed by Zhang et al. (2005). Our choice of five-min ticks interval makes consensus in the literature (see *e.g.*, Liu et al., 2015). For overnight returns, we employ a GJR-GARCH(1,1) estimator (see Glosten et al., 1993) computed on the series of stock i overnight returns.

Denoting the respective estimators as $\hat{\sigma}^{RV}_{i,d(t_{i,k})}$ and $\hat{\sigma}^{GJR}_{i,d(t_{i,k})}$ where $d(t_{i,k})$ designs the day corresponding to timestamp $t_{i,k}$, we define our standardized returns as follows:[13]

[12]To avoid zeros in the denominator of the first terms of (1), we add one to all $N_{i,t_{i,k}}$ entries.

[13]Note that to be consistent with the non-standardized returns $R_{i,t_{i,k}}$ that are expressed in daily terms, we convert these two volatility estimators to a full-day scale as well, using the multiplying factor $\sqrt{2}$.

$$r_{i,t_{i,k}} = \begin{cases} R_{i,t_{i,k}}/\hat{\sigma}^{RV}_{i,d(t_{i,k})} & \text{for an intraday return} \\ R_{i,t_{i,k}}/\hat{\sigma}^{GJR}_{i,d(t_{i,k})} & \text{for an overnight return} \end{cases}. \tag{3}$$

Table 1 presents summary statistics on our main variables: the RH users' net position openings indicator $\Delta N_{i,t_{i,k}}$, and the standardized returns $r_{i,t_{i,k}}$. These statistics are computed over the complete sample of stock and day-time observations. Panel A shows that the daily net position openings has an average of 29 basis points, indicating that the number of open positions increases by 0.29 percent per day on average. One reason that makes this average positive is the success of Robinhood: the number of RH users was almost constantly increasing during our sample period, and when a new user registers, she opens new positions to build her portfolio. The median change, however, is zero because an important number of observations do not change from one time to another. Comparing intraday and overnight activities reveals that, while the respective averages are relatively close at approximately 28 and 34 bps, RH users' trading behavior tends to be more dispersed within the day than overnight.

Panel B describes the standardized returns. The distribution of intraday and overnight returns are both centered around zero. Compared to overnight returns, the intraday returns series appears less dispersed (second moment) but its 5th and 95th percentiles suggest that it has wider tails.[14]

[Insert Table 1 about here.]

Since we aim to differentiate the trading behaviors of RH investors in response to movements of different magnitudes—notably the extreme negatives and positive ones—we classify the standardized returns into six groups based on percentiles and zero-return that form the following partition of $\mathbb{R}$: $\mathcal{G}_1 = [-\infty, 5\%[$, $\mathcal{G}_2 = [5\%, 25\%[$, $\mathcal{G}_3 = [25\%, 0[$, $\mathcal{G}_4 = [0, 75\%[$, $\mathcal{G}_5 = [75\%, 95\%[$, $\mathcal{G}_6 = [95\%, \infty]$. The groups are formed using all standardized return observations, that is, all stock and day-time observations.[15] To define a clear separation between negative and positive returns, groups $\mathcal{G}_3$ and $\mathcal{G}_4$ are based on a "hard cutoff" corresponding to a return of zero. Note that this zero-cutoff is also the median of the sample, so it would be equivalent to denote these two groups as $[25\%, 50\%[$ and $[50\%, 75\%[$. Table 2 gives more details on this classification by groups. $\mathcal{G}_1$ contains the most extreme negative standardized returns that are below -5.14. By construction, it corresponds to five percent of all observations, or 389,620 returns. Among these observations, 371,852 are intraday returns,

[14] Note that approximately 85% (15%) of the total number of observations correspond to intraday (overnight) changes ($\Delta N_{i,t_{i,k}}$) or returns ($r_{i,t_{i,k}}$), as a given stock generally counts one overnight and six hourly-spaced intraday observations per day. To mitigate the effect of potential outliers, we winsorize $\Delta N_{i,t_{i,k}}$ at the 0.5th and 99.5th percentiles. In the Internet Appendix, we provide graphical representations of these main variables and summary statistics computed with alternative versions of $\Delta N_{i,t_{i,k}}$.

[15] Alternatively, the quantiles can be identified at the stock-level, *i.e.*, separately for each stock, and/or separately for the overnight and intraday returns. The robustness section of the Internet Appendix shows that our results are similar using quantiles computed in such ways.

and 17,768 are overnight returns. Group $\mathcal{G}_3$ contains all (negative) returns that are between the 25th quantile (-1.69) and zero. Group $\mathcal{G}_4$ contains all (non-negative) returns that are between zero and the 75th quantile (1.69). All returns in the most extreme positive returns group ($\mathcal{G}_6$) have values superior or equal to 5.03.

[Insert Table 2 about here.]

3. Empirical Results

We now turn to our main analyses. First, we evaluate how RH investors respond to previous intraday and overnight returns and identify three major behaviors. Next, we analyze how these three behaviors relate to certain factors. In particular, we differentiate between trading behaviors following intraday and overnight returns, we assess the effect of the COVID-19 global pandemic on these behaviors, and we contrast them based on company characteristics such as size and industry.

3.1. The Reaction of RH Investors to Previous Intraday and Overnight Returns

We first investigate how RH investors respond to previous intraday and overnight price movements. To this end, we explore the sensitivity of our RH users' net position opening indicator to previous intraday and overnight standardized returns categorized into groups $\mathcal{G}_g$. Formally, we define the following set of six separate specifications:

$$\Delta N_{i,t_{i,k}} = \sum_{g=1}^{6} \beta_g^{(L)} I_{\mathcal{G}_g}(r_{i,t_{i,k-L}}) + \mathrm{CTRL}_{i,t_{i,k}}^{(L)} + \epsilon_{i,t_{i,k}}^{(L)}\,, \tag{4}$$

for $L = 0, \ldots, 5$, where L defines the time-lag, or number of time-step(s) between the intraday or overnight return observation $r_{i,t_{i,k-L}}$ and the net position opening observation $\Delta N_{i,t_{i,k}}$, and $I_{\mathcal{G}_g}(x)$ is an indicator function that is equal to one if $x \in \mathcal{G}_g$ and zero otherwise. To make inferences about the speed at which they react to these movements, we analyze the relationship on a contemporaneous basis ($L = 0$), and up to five time-lags ($L = 1, \ldots, 5$). Note that this time-lag can be either a one-hour intraday period (when the observations $\Delta N_{i,t_{i,k}}$ and $r_{i,t_{i,k-L}}$ are from the same day), or an overnight period (when the observations $\Delta N_{i,t_{i,k}}$ and $r_{i,t_{i,k-L}}$ are from consecutive trading days). We are interested in the estimates of $\hat{\beta}_g^{(L)}$, which measure the propensity of RH users to open new positions in stocks experiencing price movements of different magnitudes—from extremely negative to extremely positive—and for various time-lags.

We also include controls for the returns of the stock i surrounding the time-lag of interest, as they may also affect the trading behavior of RH investors. Because in some cases the response could be caused by market-wide rather than stock-specific movements, we also control for market standardized returns at zero to five time-lag(s). Formally, these controls are given by

$$\mathrm{CTRL}^{(L)}_{i,t_{i,k}} \equiv \sum_{\substack{j=0\\ j\neq L}}^{5} \left(\gamma^{(L)}_j r_{i,t_{i,k-j}} + \delta^{(L)}_j r^2_{i,t_{i,k-j}}\right) + \sum_{j=0}^{5} \left(\psi^{(L)}_j r_{M,t_{i,k-j}} + \xi^{(L)}_j r^2_{M,t_{i,k-j}}\right) , \qquad (5)$$

where the terms under the first and second summations account for stock i returns at lags zero to five but different than L and their quadratic versions ($r_{i,t_{i,k-j}}$ and $r^2_{i,t_{i,k-j}}$), and market returns at lag zero to five and their quadratic versions ($r_{M,t_{i,k-j}}$ and $r^2_{M,t_{i,k-j}}$), respectively.

Note that for all specifications in (4), the dependent variable $\Delta N_{i,t_{i,k}}$ remains the same and the market-returns controls $r_{M,t_{i,k-j}}$ and $r^2_{M,t_{i,k-j}}$ are also fixed. What vary between specifications is, first, the categorical variable $I_{\mathcal{G}_g}(r_{i,t_{i,k-L}})$ and second, the stock-returns controls $r_{i,t_{i,k-j}}$ and $r^2_{i,t_{i,k-j}}$ because they all depend on the time-lag L of interest. For example, in specification $L = 0$, we evaluate the relationship between RH users' net position openings and contemporaneous returns, controlling for the returns at lags $L = 1, \ldots, 5$. In specification $L = 1$, we evaluate the relationship between RH users' net position openings and one time-lag returns, controlling for the returns at lags $L = 0, 2, \ldots, 5$, and so on.[16]

Table 3 presents the estimates for all specifications, which are also summarized visually in Figure 1. For each specification, the estimates are based on the complete sample of stock and day-time observations and estimated by pooled OLS, and the standard errors are clustered at the stock dimension and corrected for heteroskedasticity.[17] These results point out to three specific behaviors exhibited by RH investors after observing intraday and overnight returns.

[Insert Table 3 and Figure 1 about here.]

Behavior #1: RH investors respond strongly to large negative price movements. Panel A of Figure 1 shows the estimates as a function of different return categories. For all time-lags, it appears that RH investors tend to open new positions in stocks that experience large negative movements during the day or overnight. Indeed, for all specifications, the highest estimate is associated with the most negative group (<5%). After one time-lag ($L = 1$), the response is particularly strong, at more than 100 bps. This implies that during the first time-step following a very negative overnight or intraday return on a given stock, the number of RH users opening new positions in that stock increases by about one percent per day.

Behavior #2: Asymmetric response to extreme price movements. Panel A of Figure 1 also shows that, for all non-contemporaneous regressions ($L \neq 0$), we observe asymmetric

[16] With these dynamic controls, estimating these six regressions separately is almost equivalent to estimating a single regression that would include all categorical variables. However, because it would incorporate multiple categorical variables, such a specification would yield uninterpretable estimates $\hat{\beta}^{(L)}_g$. Because the controls included in each of the six specifications are a way to "control for the other specifications," these six separate specifications should not be viewed as independent but rather like a system.

[17] Our choice to cluster standard errors is partially motivated by Petersen (2009). Because we use returns that are standardized on a daily basis, we do not cluster the standard errors at the day-time dimension. Our correction for heteroskedasticity is based on the "HC3" method (see White, 1980; Zeileis, 2004).

U-shaped patterns. This tells us that RH investors also tend to open new positions in sharply rising stocks (those with previous extreme positive returns), but to a lesser extent compared to sharply declining stocks. It implies that, in general, extreme returns in the negative territory (with a standardized value below -5.16) will attract more attention in the RH community than those in the positive territory (with a standardized value above 5.03). As mentioned in the introduction, using daily frequency data, Barber et al. (2022) find that RH investors tend not to differentiate between previous gainers and losers when they are included in the top movers' list displayed in the RH smartphone app. In contrast, in our high-frequency settings and using a universe of all common stocks available to trade in the RH platform, we find that this buying behavior is significantly more directed towards large losers than gainers. This is also in contrast to the findings of Welch (2022) who observes an asymmetry in the other direction (favoring gainers).

Behavior #3: RH investors are particularly rapid to respond to large negative returns. Panel B of Figure 1 displays the estimates as a function of the time-lag. For the most negative group (<5%), the curve is monotonically decreasing from time-lags one to five. It indicates that the response of RH investors to large negative movements is strongest during the first time-step after the movement and tends to weaken as time passes: during the first time-step following the large decline on a given stock, the number of RH users holding this stock increases by approximately one percent per day while during the fifth time-step, the increase stands at only 0.60 percent per day. In addition, the movements of other magnitude and signs (*i.e.*, from groups [25%-0[to ≥95%) are not characterized by this high speed of response, as position openings are more evenly distributed across the first, second, third, fourth, and fifth time-steps that follow the movement. Hence, this high speed of response seems specific to large negative returns.

It is interesting to see that all these behaviors have something in common: they relate to extremely negative price movements. In contrast, no strong behavioral pattern emerges for other types of movements (*e.g.*, moderate, extremely positive). Therefore, it appears that the RH community pays special attention to these extreme downward movements: they tend to purchase stocks that are falling sharply during the day or overnight. This observation is also supported by the fact that, for the large negative return group (dark red curve) in Panel B of Figure 1, the estimate is much lower for the contemporaneous regression ($L = 0$) compared to the one-time-lag regression ($L = 1$). This large difference (100 vs. 38 bps) might imply that RH investors are particularly attuned to large negative movements. If the estimates were similar for $L = 0$ and $L = 1$, it would indicate that the large negative movement had no impact on their trading behaviors. However, the much higher estimate at $L = 1$ could suggest that these large negative movements prompt a change in behavior, possibly resulting in new position openings.[18]

[18]Conversely, the other return groups do not exhibit the same patterns as they have lower pairwise differences (*e.g.*, 45 bps vs. 35 bps for the $[5\% - 25\%[$ group or 41 bps vs. 32 bps for the $\geq 95\%$ group).

3.2. Contrasting the Behaviors with Key Determinants

The above analysis provides general results on the trading behavior of RH investors with respect to all types of returns (*i.e.* overnight and intraday), over a period of more than two years, and a broad universe of more than 2,500 stocks. To gain a more refined understanding, we now evaluate these behaviors under specific conditions. Specifically, we investigate four factors that we believe are relevant to the analysis. First, we ask whether these behaviors differ if the observed price movement occurs overnight or intra-daily. Second, we evaluate the impact of a major shock on these behaviors: the announcement of the COVID-19 global pandemic. Third, we differentiate these behaviors based on the market capitalization of the stocks. Fourth, we assess the heterogeneity of these behaviors across industries.

3.2.1. Methodological Framework

To conduct these analyses, we propose a modified version of the regressions in (4) that enables us to differentiate the trading behavior of RH users based on the factors discussed above. Formally, we introduce a second categorical variable $I_{CRIT_c}(r_{i,t_{i,k-L}})$ that takes the value of one if $r_{i,t_{i,k-L}}$ meets a classification criterion $CRIT_c$ and zero otherwise. The specifications are:

$$\Delta N_{i,t_{i,k}} = \sum_{g=1}^{6}\sum_{c=1}^{C} \beta_{g,c}^{(L)} I_{\mathcal{G}_g}(r_{i,t_{i,k-L}}) \cdot I_{CRIT_c}(r_{i,t_{i,k-L}}) + \mathrm{CTRL}_{i,t_{i,k}}^{(L)} + \epsilon_{i,t_{i,k}}^{(L)}\,, \tag{6}$$

for $L = 0, \ldots, 5$, where the classification criterion $CRIT$ contains $C \geq 2$ levels.[19]

Additionally, to effectively contrast the three behaviors identified in the main results based on a given classification criterion, we establish the following proxies, which are linear combinations of the estimates obtained in (6):

$$\begin{aligned}
&\textit{Behavior \#1: ExtNeg}_c^{(L)} \equiv \hat{\beta}_{<5\%,c}^{(L)} - 0.5\left(\hat{\beta}_{[25\%,0[,c}^{(L)} + \hat{\beta}_{[0,75\%[,c}^{(L)}\right) \;\; \forall L, c \\
&\textit{Behavior \#2: Asy}_c^{(L)} \equiv \hat{\beta}_{<5\%,c}^{(L)} - \hat{\beta}_{\geq 95\%,c}^{(L)} \;\; \forall L, c \\
&\textit{Behavior \#3: SpeedExtNeg}_c \equiv \hat{\beta}_{<5\%,c}^{(L=1)} - \hat{\beta}_{<5\%,c}^{(L=5)} \;\; \forall c
\end{aligned} \tag{7}$$

The metric *ExtNeg* quantifies the strength with which RH investors respond to large negative returns relative to moderate returns. *Asy* measures the propensity of RH investors to buy sharply declining stocks relative to sharply rising stocks, that is, how asymmetric is their response to extreme returns. *SpeedExtNeg* evaluates their speed of response to large downward price movements. We measure it as the difference in the strength of the responses at one and five time-lags, so a higher value indicates a faster response.

3.2.2. Overnight Versus Intraday Returns

We begin by distinguishing the behaviors based on the type of returns. Do RH investors open more or fewer positions if the movement occurs overnight or during trading hours? Is the

[19] For example, our type-of-returns classification criterion has $C = 2$ levels: overnight returns and intraday returns; our size classification criterion has $C = 3$ levels: small-cap, mid-cap and large-cap.

asymmetric response to extreme price movements stronger or weaker after an overnight vs. intraday movement? Do they respond faster to a "pre-market" or intraday extreme negative movement? Formally, we address these questions using a two-level classification criterion ($C = 2$) that identifies whether the return observation is overnight or intraday. We estimate the regressions in (6) and obtain 6×2 estimates for each time-lag L, enabling us to analyze the behavior of RH investors separately for each type of return.

Figure 2 presents estimation results. The difference of magnitude for the response to extreme returns is striking. For instance, an hour after observing a very negative *overnight* return on a given stock, the number of RH users holding this stock increases by approximately 5.73 percent per day. In contrast, the highest intraday-returns estimate across all regressions is about seven times lower at only 0.78 percent.[20]

[Insert Figure 2 about here.]

A visual examination of this figure indicates that all of our key behaviors are more pronounced for overnight returns. In Table 4, we present the values of our behavior proxies defined in (7) and confirm this observation.

(#1) Panel A focuses on the strength of the response to extreme negative returns (*ExtNeg*). After one time-lag ($L = 1$), the response to large negative overnight movements is very strong, representing a net position openings that is 581 bps superior than for a moderate movement. This is more than thirteen times stronger than the response to large negative intraday movements (0.43 percent per day). According to Wald tests, individually, these two responses are significantly positive, and their difference is also significantly positive at the one percent level. Furthermore, the same interpretation holds for all regressions, that is, all time lags. Overall, these results suggest that, for the same level of extreme negative movements (a standardized return below -5.14), RH investors open more new positions if this return occurs overnight instead of intraday.

(#2) Panel B contrasts the second behavior related to the asymmetric response to extreme returns. For all non-contemporaneous time-lags ($L \neq 0$), the differences are significant and positive, confirming that the asymmetry is more pronounced for overnight returns. It means that when a large movement occurs during trading hours, RH investors tend not to differentiate between an upward or downward change (*i.e.*, their buying behavior is more balanced), but when a large movement occurs overnight, they react primarily to downward moves (*i.e.*, their buying behavior is more skewed toward the big overnight losers).

(#3) Panel C demonstrates that the speed of response to large negative returns is also exacerbated for overnight returns. We measure this speed at 223 bps for overnight returns and 32 bps for intraday returns. The behaviors are individually significant, and the difference of 191 bps is substantial and significant.[21] Therefore, RH investors tend to respond more

[20] For more details on estimation results, see the Internet Appendix

[21] Because comparing behaviors #3 involves estimates from different regressions, we perform the Wald tests using a variance-covariance matrix that assumes zero-covariances between the estimates that come from different regressions.

quickly to large downward overnight price movements relative to large downward intraday price movements.

[Insert Table 4 about here.]

3.2.3. Impact of the COVID-19 Global Pandemic Announcement

On March 11, 2020, the World Health Organization declared the outbreak of COVID-19 a global pandemic, leading to widespread lockdowns and an increase in individuals investing in the stock market. In particular, the Robinhood platform saw a significant influx of new traders during this period.[22] For some observers, through the provision of new liquidity, these new traders acted as a "market-stabilizing force" (Welch, 2022) and certainly contributed to the quick recovery that followed the COVID-19 stock market crash (World Economic Forum, 2022). In addition, this event triggered a significant and sustained increase in the level of volatility in the markets, resulting in more frequent instances of extreme price movements. In this section, we examine how such a shock has affected the key RH investors' behaviors identified in the main results. We use a classification criterion that contains two levels ($C = 2$), identifying whether the return observation falls in the pre-announcement period, from June 01, 2018 to March 10, 2020, or post-announcement period, from March 11, 2020 to August 13, 2020.[23]

As illustrated in Figure 3, our estimates demonstrate that, as previously noted by Ozik et al. (2021), there was a dramatic increase in the overall activity of RH traders following the COVID-19 pandemic announcement. In fact, the average of the dependent variable $\Delta N_{i,t_{i,k}}$ unconditional of the return group level is more than 3.5 times higher post-announcement. Moreover, all post-announcement estimates are significantly higher than their pre-announcement counterparts, indicating that RH investors have acquired more stocks in the post-announcement period.

[Insert Figure 3 about here.]

In Table 5, we contrast the general behaviors identified earlier according to this criterion.[24]

(#1) RH investors' response to extreme negative returns is strong both in the pre- and post-announcement periods, as evidenced by the generally positive and significant values of *ExtNeg*. However, for all time-lags, the strength of this behavior is significantly higher in the post-announcement period. For instance, prior to the announcement, one time-step after observing a large negative return on a given stock, the number of Robinhood users holding this stock increased by approximately 71 bps more than if they observed a moderate return. After the announcement, the corresponding increase stands at 100 bps. This 29 bps

[22] See *e.g.*, CNBC Markets [url1, url2].

[23] Alternative choices of period length can be considered. In particular, one could define periods of equal length before and after the announcement date, using ± 3 or ± 6 months surrounding the announcement date. Results with these alternatives are provided in the robustness section of the Internet Appendix.

[24] For more details on estimation results, see the Internet Appendix.

difference is significant at the one percent level. In sum, RH investors have been opening more new positions on falling stocks in the post-announcement period.

(#2) Our findings regarding the asymmetry of response to extreme returns are more mixed. Although we do observe this asymmetry both in the pre- and post-periods (with almost all $Asy^{(L)}$ being positive and significant), the Pre−Post differences are only statistically significant for half of the time-lags ($L = 1, 3, 4$) and have different signs. This suggests that the impact of the COVID-19 pandemic announcement on this behavior, if any, is relatively minor.

(#3) The speed of response to large negative returns has increased after the COVID-19 pandemic announcement. Individually, these speeds are statistically significant, indicating that both pre- and post-announcement, RH investors were particularly quick to respond to large negative returns (faster than for any other type of movement). However, the difference in speed between the post- and pre-announcement periods (17 bps) is large and statistically significant, implying that Robinhood investors tended to respond more rapidly to large downward price movements in the post-period.

[Insert Table 5 about here.]

3.2.4. Decomposing Key Behaviors by Company Size

It is not clear whether retail investors prefer trading smaller- or larger-capitalization stocks. While small-cap stocks are typically less expensive, which may make them more attractive to individual investors with limited portfolio depth (see *e.g.*, AMF Report, 2021), the increasing availability of fractional stock trading (see *e.g.*, Gempesaw et al., 2022) has rendered this argument less compelling. Some studies suggest that retail investors possess a comparative advantage in trading small stocks (Kelley and Tetlock, 2013; Jirajaroenying et al., 2019) and exhibit stronger herding behavior on such stocks (Venezia et al., 2011; Hsieh et al., 2020). In contrast, in his study dedicated to Robinhood investors, Welch (2022) finds that they do not particularly hold small stocks. On the contrary, their typical portfolio is relatively close to the market portfolio, that is, composed primarily of large-cap stocks.

We complete this discussion by contrasting our three behaviors by firm size. We utilize market capitalization data to categorize, on a daily basis, the stocks in our sample into three distinct size categories: small-capitalization (<\$2 billion), mid-capitalization (\$2 billion to \$10 billion), and large-capitalization (>\$10 billion).[25] Then, we estimate the regressions

[25] We obtain share prices and the number of shares outstanding through CRSP, from which we calculate the market capitalization, taking into account any necessary adjustments for stock splits. Because we could not retrieve information for ten stocks, our sample is reduced to 2,575 stocks (or 7,743,575 observations) for this analysis. The Financial Industry Regulatory Authority (FINRA) provides size thresholds that are used to divide the universe of stocks into five categories, including micro-cap and mega-cap [url]. In our analysis, we classify micro-cap stocks as small-cap and mega-cap stocks as large-cap. It is important to note that the stock size category assignment is done on a daily basis. As a result, a specific stock may move between categories throughout the period. For further details on the distribution of stocks by size category and estimation results, see the Internet Appendix.

in (6) using this size criterion ($C = 3$). As for the previous criteria, we present estimation results in Figure 4 and compare the respective behaviors in Table 6.

(#1) Panel A of Table 6 shows that, for the first non-contemporaneous time-lags ($L = 1, 2$), the largest values of *ExtNeg* are associated with large-cap stocks. The Wald tests confirm this pattern, as the response is statistically more pronounced for the large-cap category in comparison to the mid-cap (one percent level) and small-cap (five percent level) categories. Interestingly, the differences in the responses are also positives between the small- and mid-cap categories and significant at the five percent level, but less so than the large- vs. mid-cap differences (*e.g.*, for $L = 1$, Small−Mid = 7.83 and Large−Mid = 16.26). These facts suggest that RH investors primarily focus on extremely negative returns of large stocks, followed by those of small stocks, with the mid-size category coming last.[26]

(#2) Panel B of Table 6 demonstrates that, for all non-contemporaneous time-lags, Asy increases monotonically with stock size. It means that the inclination of RH investors to open more new positions in the big losers compared to big gainers is significantly more pronounced for large-cap stocks compared to mid-cap stocks—and for mid-cap stocks compared to small-cap stocks. In fact, Figure 4 also illustrates this point: for the large-cap category (Panel C) and the one-time-lag regression (green line) this asymmetry is so much more pronounced that the estimates decrease monotonically with return group levels. Put differently, RH investors respond more strongly to large negative returns than to moderate returns, and also more strongly to moderate returns than to large positive returns.

(#3) The large-cap category is also characterized by a higher speed of response to large negative returns compared to smaller stocks. Indeed, the differences in Panel C of Table 6 (Large−Mid and Large−Small) are positive and significant at the one percent level. Therefore, after a large-cap (mid-cap or small-cap) stock posts an extremely negative return, it takes RH investors less (more) time to open new positions in that stock. Comparing small- and mid-cap stocks, however, tells us that the speed is similar for these two categories (no statistical significance below ten percent level).

[Insert Table 6 and Figure 4 about here.]

3.2.5. Decomposing Key Behaviors by Industry

In our last criterion-based analysis, we study the heterogeneity of the behaviors across industries. We identify stock i's industry as per the General Industrial Standard Classification (GICS) that divides the universe into eleven sectors ($C = 11$), and estimate the regressions in (6) accordingly.[27] Due to the large number of categories, the analysis becomes quite extensive. Therefore, we relegate estimation results and individual Wald tests on each behavior

[26] Note that, in contrast, no pattern emerges at larger delays ($L = 3, 4, 5$): the differences in *ExtNeg* between categories either lack statistical significance or show opposite signs. For example, Large−Small for $L = 4$ is negative with five percent level significance.

[27] We obtain information on GICS sectors through COMPUSTAT. Because we could not retrieve information for 85 stocks, our sample is reduced to 2,500 stocks (or 7,434,949 observations) for this analysis. For more information on the distribution of stocks and observations per sector, and details on estimation results, see the Internet Appendix.

per industry to the Internet Appendix. Instead, Figure 5 displays the value of our behavior proxy per industry, and Table 7 reports Wald tests that compare the value of our behavior proxy per industry to the average value of all other ten industries.

(#1) In Panel A of Figure 5, for all non-contemporaneous time-lags, we observe that the value of *ExtNeg* is the highest for stocks in the Energy, Consumer Discretionary and Health Care sectors. Furthermore, Table 7 indicates that the differences between these quantities and the average of the remaining ten sectors are significant at the five percent level or lower (with the exception of Energy for $L = 5$). This suggests that RH investors tend to be more attracted to large negative returns from stocks in these sectors: they open more positions in falling Energy, Consumer Discretionary, and Health Care stocks compared to falling stocks from other sectors. Conversely, the value of *ExtNeg* is significantly below the average for the Financials and Utilities sectors, indicating that RH investors may pay less attention to falling stocks from these sectors.

(#2) Two of the sectors discussed above, Energy and Consumer Discretionary, also stand out in Panel B of Figure 5. For most time-lags, the asymmetric behavior of RH investors towards extreme movers is the strongest for these sectors. Statistically, the value of our proxy *Asy* specific to Consumer Discretionary stocks is significantly above the average of the other ten sectors (at five percent level or below). Regarding stocks from the Energy sector, *Asy* is significantly stronger than the average for time-lags one and two only (one percent level). Additionally, for all time-lags, the Health Care sector is characterized by the lowest value of *Asy*, indicating that the attitude of RH investors towards extreme movers from the Health Care sector is more symmetric.

(#3) Panel C of Figure 5 shows that RH investors tend to respond particularly fast to stocks from the Energy sector that experience large negative returns. Again, for this sector, the value of our proxy *SpeedExtNeg* is the highest and stands out significantly above the average at the one percent level. In contrast, the other sectors are closer to the average: most are not statistically different from the average, with the exception of Consumer Discretionary (Industrials), which is above (below) the average at the ten percent level.

[Insert Figure 5 and Table 7 about here.]

4. Conclusion

The typical RH investor is unlike any other. He is younger and less experienced than the average retail investor. More important, as a millennial, he is very tech-savvy and fully immersed in the digital society. Arguing that such a special profile makes this new community of investors more inclined to engage in intra-day trading, we offer a comprehensive study on the relationship between their trading behavior and previous overnight and intraday returns.

We identify three key trading behaviors. First, RH investors tend to open new positions in stocks that experience large negative intraday or overnight movements—more than in stocks with any other type of movements (moderate, positive, very positive). Second, their purchase behavior towards extreme intraday and overnight movers is asymmetric, showing a preference for big losers compared to big gainers. Third, they are particularly quick to trade after large negative movements: when a stock sharply drops during the day or overnight, RH investors tend open new positions in that stock in the first hour following the movement, with far fewer position openings in the subsequent hours. In comparison, this rapidity is not observed with regard to other types of movement (returns closer to zero or even large positive returns). As all these three behaviors are directly related to large negative movements, our results point out that RH investors are particularly attuned to sharply declining stocks during the day or overnight.

We also demonstrate that these behaviors can vary under certain conditions. Contrasting them by type-of-returns (overnight vs. intraday), we find that all behaviors are more pronounced for overnight movements: RH investors tend to open more (fewer) new positions on stocks that are sharply declining overnight (intraday); their response to extreme returns is more (less) asymmetric when the movement occurs overnight (intraday), and they are faster (slower) at opening new positions after large negative overnight (intraday) movements. Splitting our sample into pre- and post-COVID-19 announcement periods further reveals that two behaviors are exacerbated post-COVID: the response to large negative movements and the speed of response to large negative movements. Furthermore, it appears that RH investors pay more attention to large-cap companies compared to mid- or small-cap companies, and stocks from the Energy and Consumer Discretionary sectors compared to other sectors. Indeed, most of the three behaviors are exacerbated for stocks with these features.

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Table 1: Summary Statistics of Main Variables

The summary statistics are calculated using the complete sample of stock and day-time observations. Panel A describes our proxy for Robinhood users' trading behavior $\Delta N_{i,t_{i,k}}$ defined in (1), winsorized at the 0.5 and 99.5 percentiles, and expressed in basis points. Panel B describes standardized returns $r_{i,t_{i,k}}$ defined in (3). All statistics are expressed in daily units. *Nobs*, T and # represent the number of observations, trading days, and companies, respectively.

Panel A: RH Users' Net Position Openings $\boldsymbol{\Delta N_{i,t_{i,k}}}$										
	Av	Std	5th	25th	50th	75th	95th	*Nobs*	T	#
Intraday	28.02	607.05	-675.70	-35.93	0.00	26.53	797.60	6,589,523	527	2,585
Overnight	34.32	336.60	-254.59	-37.63	0.00	58.14	380.96	1,202,863	526	2,585
All	29.00	573.69	-606.40	-36.65	0.00	39.21	726.68	7,792,386	527	2,585
Panel B: Standardized Returns $\boldsymbol{r_{i,t_{i,k}}}$										
	Av	Std	5th	25th	50th	75th	95th	*Nobs*	T	#
Intraday	-0.02	3.22	-5.38	-1.90	0.00	1.88	5.27	6,589,523	527	2,585
Overnight	0.02	4.26	-3.04	-0.89	0.02	0.98	3.02	1,202,863	526	2,585
All	-0.02	3.40	-5.14	-1.69	0.00	1.69	5.03	7,792,386	527	2,585

Table 2: Classification of Standardized Returns

Panel A shows the breakdown of the groups by percentile cutoffs (PRCT range) and their corresponding quantile values ($r_{i,t_{i,k}}$ range). To define a clear separation between negative and positive returns, groups $\mathcal{G}_3$ and $\mathcal{G}_4$ are based on a "hard cutoff" corresponding to a return of zero. Panel B displays the number of observations within each group.

Panel A: Group Definitions						
	$\mathcal{G}_1$	$\mathcal{G}_2$	$\mathcal{G}_3$	$\mathcal{G}_4$	$\mathcal{G}_5$	$\mathcal{G}_6$
PRCT range	$< 5\%$	[5%-25%[	[25%-0[	[0-75%[	[75%-95%[	$\geq 95\%$
$r_{i,t_{i,k}}$ range	< -5.14	$[-5.14, -1.69[$	$[-1.69, 0.00[$	$[0.00, 1.69[$	$[1.69, 5.03[$	≥ 5.03

Panel B: Number of Observations						
	$\mathcal{G}_1$	$\mathcal{G}_2$	$\mathcal{G}_3$	$\mathcal{G}_4$	$\mathcal{G}_5$	$\mathcal{G}_6$
Intraday	371,852	1,416,773	1,322,808	1,699,697	1,405,809	372,584
Overnight	17,768	141,704	415,630	458,057	152,668	17,036
All	389,620	1,558,477	1,738,438	2,157,754	1,558,477	389,620

Table 3: The Impact of Overnight and Intraday Returns on RH Users' Trading Decisions
This table shows the $\hat{\beta}_g^{(L)}$ estimates obtained from the regressions in (4). The six regressions are all based on the complete sample of stock and day-time observations and are estimated by pooled OLS. Estimates are expressed in basis points. Associated t-statistics are shown in parenthesis. The standard errors are clustered at the stock level and corrected for heteroskedasticity.

	Time-Lag					
	$L = 0$	$L = 1$	$L = 2$	$L = 3$	$L = 4$	$L = 5$
<5%	37.75	100.38	85.70	74.04	65.98	59.66
	(20.6)	(58.56)	(55.96)	(53.04)	(50.27)	(47.12)
[5%-25%[	34.94	45.10	42.96	40.14	37.16	35.16
	(34.81)	(45.59)	(46.60)	(45.01)	(42.81)	(40.77)
[25%-0[	35.38	24.67	27.70	27.56	27.71	28.62
	(43.58)	(28.01)	(32.51)	(32.13)	(32.39)	(34.07)
[0-75%[	29.54	24.09	23.96	25.58	26.59	27.60
	(37.96)	(28.69)	(28.41)	(29.91)	(31.34)	(32.8)
[75%-95%[	30.02	27.52	28.32	30.73	33.19	33.33
	(30.66)	(28.05)	(30.40)	(34.03)	(37.26)	(37.03)
≥95%	32.08	40.53	43.46	44.58	47.11	51.48
	(15.87)	(22.24)	(27.57)	(30.77)	(34.01)	(36.98)
$Adj.R^2$	0.001	0.002	0.001	0.001	0.001	0.001
Nobs	7,779,461	7,779,461	7,779,461	7,779,461	7,779,461	7,779,461

Table 4: Decomposing Key Behaviors by Type of Returns – Overnight vs. Intraday
Based on the $\hat{\beta}_{g,c}^{(L)}$ estimates obtained from the regressions in (6), this table compares the key behaviors using the type-of-return classification criterion. In each Panel, the first two rows report the value of our behavior proxy, defined in (7), specific to overnight and intraday returns, respectively, and the last row takes the difference. The stars associated with each quantity represent the level of significance ($^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.10$) for which a Wald test is rejected. For all tests, the null hypothesis is that the evaluated quantity equals zero.

Panel A: Strength of Response to Extreme Negative Returns (*ExtNeg*)

	Time-Lag					
	$L=0$	$L=1$	$L=2$	$L=3$	$L=4$	$L=5$
OV	217.10^{***}	580.54^{***}	456.28^{***}	386.31^{***}	371.39^{***}	330.45^{***}
INT	-7.24^{***}	43.91^{***}	35.19^{***}	27.50^{***}	20.02^{***}	14.81^{***}
(OV−INT)	224.34^{***}	536.63^{***}	421.09^{***}	358.81^{***}	351.37^{***}	315.64^{***}

Panel B: Asymmetry of Response to Extreme Returns (*Asy*)

	Time-Lag					
	$L=0$	$L=1$	$L=2$	$L=3$	$L=4$	$L=5$
OV	-79.91^{***}	131.98^{***}	89.87^{***}	87.20^{***}	95.47^{***}	103.62^{***}
INT	9.17^{***}	55.49^{***}	39.23^{***}	26.05^{***}	14.62^{***}	3.10^{**}
(OV−INT)	-89.08^{***}	76.49^{***}	50.64^{***}	61.15^{***}	80.85^{***}	100.53^{***}

Panel C: Speed of Response to Extreme Negative Returns (*SpeedExtNeg*)

OV	223.03^{***}
INT	32.47^{***}
(OV−INT)	190.56^{***}

Table 5: Decomposing Key Behaviors Pre- and Post-COVID-19 Pandemic Announcement
Based on the $\hat{\beta}^{(L)}_{g,c}$ estimates obtained from the regressions in (6), this table compares the key behaviors using the pre- vs. post-COVID-19 pandemic announcement classification criterion. In each Panel, the first two rows report the value of our behavior proxy, defined in (7), specific to the pre- and post-period, respectively, and the last row takes the difference. The stars associated with each quantity represent the level of significance ($^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.10$) for which a Wald test is rejected. For all tests, the null hypothesis is that the evaluated quantity equals zero.

Panel A: Strength of Response to Extreme Negative Returns (*ExtNeg*)

	Time-Lag					
	$L = 0$	$L = 1$	$L = 2$	$L = 3$	$L = 4$	$L = 5$
Pre-COVID-19	0.11	70.88^{***}	58.19^{***}	45.4^{***}	37.96^{***}	28.97^{***}
Post-COVID-19	29.24^{***}	100.06^{***}	67.45^{***}	56.73^{***}	42.34^{***}	43.00^{***}
(Pre−Post)	-29.12^{***}	-29.18^{***}	-9.26^{***}	-11.34^{***}	-4.37^{*}	-14.03^{***}

Panel B: Asymmetry of Response to Extreme Returns (*Asy*)

	Time-Lag					
	$L = 0$	$L = 1$	$L = 2$	$L = 3$	$L = 4$	$L = 5$
Pre-COVID-19	7.30^{**}	54.22^{***}	41.41^{***}	27.99^{***}	20.88^{***}	7.25^{***}
Post-COVID-19	0.39	86.08^{***}	46.17^{***}	36.18^{***}	10.32^{***}	12.54^{***}
(Pre−Post)	6.91	-31.86^{***}	-4.76	-8.19^{**}	10.56^{***}	-5.29

Panel C: Speed of Response to Extreme Negative Returns (*SpeedExtNeg*)

Pre-COVID-19	37.74^{***}
Post-COVID-19	55.16^{***}
(Pre−Post)	-17.42^{***}

Table 6: Decomposing Key Behaviors by Company Size
Based on the $\hat{\beta}_{g,c}^{(L)}$ estimates obtained from the regressions in (6), this table compares the key behaviors using the market capitalization classification criterion. In each Panel, the first three rows report the value of our behavior proxy, defined in (7), specific to small-, mid- and large-cap stocks, respectively, and the last rows show the pairwise differences. The stars associated with each quantity represent the level of significance ($^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.10$) for which a Wald test is rejected. For all tests, the null hypothesis is that the evaluated quantity equals zero.

Panel A: Strength of Response to Extreme Negative Returns (*ExtNeg*)

	Time-Lag					
	$L = 0$	$L = 1$	$L = 2$	$L = 3$	$L = 4$	$L = 5$
Small	11.80^{***}	77.35^{***}	60.94^{***}	47.69^{***}	41.43^{***}	34.74^{***}
Mid	-6.49^{**}	69.52^{***}	54.83^{***}	48.51^{***}	36.63^{***}	28.14^{***}
Large	0.79	85.77^{***}	67.50^{***}	46.91^{***}	35.09^{***}	26.88^{***}
(Mid−Small)	-18.28^{***}	-7.83^{**}	-6.11^{**}	0.82	-4.80^{*}	-6.60^{***}
(Large−Mid)	7.28^{*}	16.26^{***}	12.67^{***}	-1.59	-1.55	-1.26
(Large−Small)	-11.01^{***}	8.43^{**}	6.56^{**}	-0.78	-6.34^{**}	-7.85^{***}

Panel B: Asymmetry of Response to Extreme Returns (*Asy*)

	Time-Lag					
	$L = 0$	$L = 1$	$L = 2$	$L = 3$	$L = 4$	$L = 5$
Small	8.02^{**}	42.54^{***}	26.95^{***}	17.68^{***}	10.25^{***}	0.88
Mid	-0.78	72.38^{***}	54.03^{***}	42.22^{***}	28.61^{***}	15.59^{***}
Large	7.05	104.66^{***}	80.79^{***}	53.24^{***}	36.09^{***}	23.11^{***}
(Mid−Small)	-8.81	29.83^{***}	27.08^{***}	24.54^{***}	18.36^{***}	14.71^{***}
(Large−Mid)	7.83	32.29^{***}	26.76^{***}	11.02^{**}	7.48^{*}	7.52^{**}
(Large−Small)	-0.97	62.12^{***}	53.84^{***}	35.56^{***}	25.84^{***}	22.23^{***}

Panel C: Speed of Response to Extreme Negative Returns (*SpeedExtNeg*)

Small	37.28^{***}
Mid	39.36^{***}
Large	57.17^{***}
(Mid−Small)	2.08
(Large−Mid)	17.82^{***}
(Large−Small)	19.90^{***}

Table 7: Decomposing Key Behaviors by Industry

Based on the $\hat{\beta}^{(L)}_{g,c}$ estimates obtained from the regressions in (6), this table compares the key behaviors using the GICS sector classification criterion. Each panel reports the value of our behavior proxy per industry, defined in (7), relative to the average value of all other ten industries. Formally, it is given by $(Proxy^{(L)}_c - \sum_{c' \neq c}^{11}(Proxy^{(L)}_{c'}/10))$. The stars associated with each quantity represent the level of significance ($^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.10$) for which a Wald test is rejected. For all tests, the null hypothesis is that the evaluated quantity equals zero.

Panel A: Strength of Response to Extreme Negative Returns (*ExtNeg*)

	Time-Lag					
	$L = 0$	$L = 1$	$L = 2$	$L = 3$	$L = 4$	$L = 5$
Energy	22.21^{***}	33.11^{***}	33.78^{***}	15.34^{***}	11.44^{**}	5.91
Materials	4.15	0.97	-7.27	-4.40	7.17	0.40
Industrials	-5.88	-12.05^{***}	-3.61	-3.87	2.92	1.06
Cons. Disc.	4.27	30.03^{***}	19.45^{***}	11.00^{***}	12.48^{***}	16.88^{***}
Cons. Staples	4.08	7.85	1.71	5.17	1.80	9.81^{*}
Health Care	-26.91^{***}	16.61^{***}	18.16^{***}	8.76^{***}	9.76^{***}	8.46^{***}
Financials	17.22^{***}	-21.18^{***}	-12.84^{***}	-8.59^{**}	-17.53^{***}	-15.41^{***}
Inf. Tech.	-38.92^{***}	-11.23^{***}	-3.02	-3.33	-6.12^{**}	-7.23^{**}
Com. services	-7.91	0.79	5.20	-2.15	5.68	2.50
Utilities	-0.56	-24.07^{***}	-20.6^{***}	-18.33^{***}	-18.67^{***}	-20.60^{***}
Real Estate	28.27^{*}	-20.81^{*}	-30.96^{***}	0.39	-8.93	-1.79

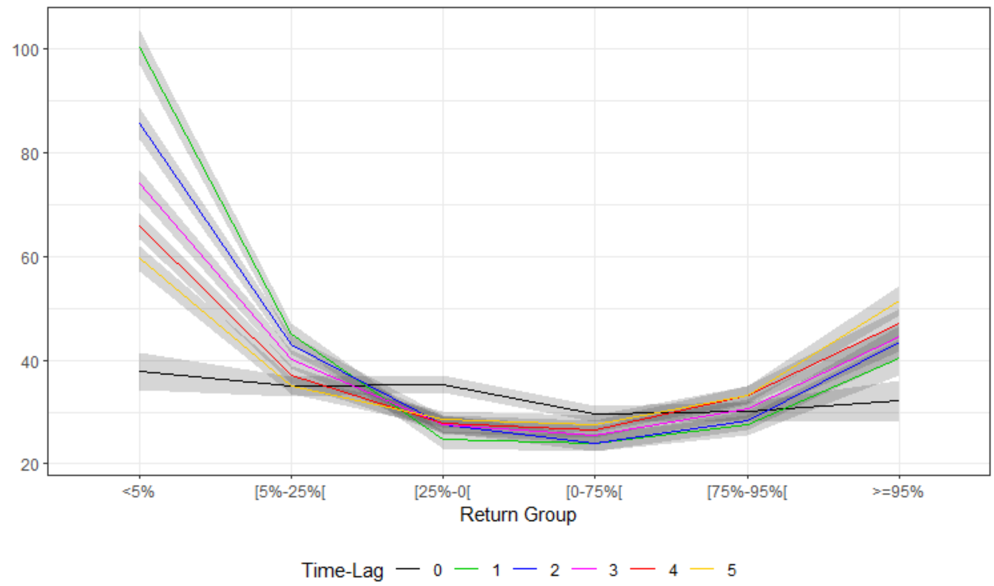
Panel B: Asymmetry of Response to Extreme Returns (*Asy*)

	Time-Lag					
	$L = 0$	$L = 1$	$L = 2$	$L = 3$	$L = 4$	$L = 5$
Energy	16.18	27.5^{***}	27.00^{***}	6.68	9.63	-4.36
Materials	14.14	9.95	5.90	1.74	8.21	6.90
Industrials	-8.43	-4.41	6.53	-2.64	13.68^{***}	5.07
Cons. Disc.	4.39	38.46^{***}	23.83^{***}	11.78^{**}	11.86^{**}	14.95^{***}
Cons. Staples	22.10^{*}	21.14^{*}	4.03	9.21	-3.78	11.48
Health Care	-68.18^{***}	-44.87^{***}	-25.84^{***}	-28.11^{***}	-19.24^{***}	-17.25^{***}
Financials	34.11^{***}	4.32	9.84^{*}	6.77	-1.72	-1.10
Inf. Tech.	-56.25^{***}	-23.69^{***}	-8.17	-7.79	-11.61^{**}	-9.38^{**}
Com. services	-26.58^{**}	-12.76	-8.92	-10.18	-6.93	-1.28
Utilities	13.68	10.05	2.34	2.17	2.93	-14.41^{*}
Real Estate	54.84^{**}	-25.68	-36.55^{**}	10.39	-3.04	9.39

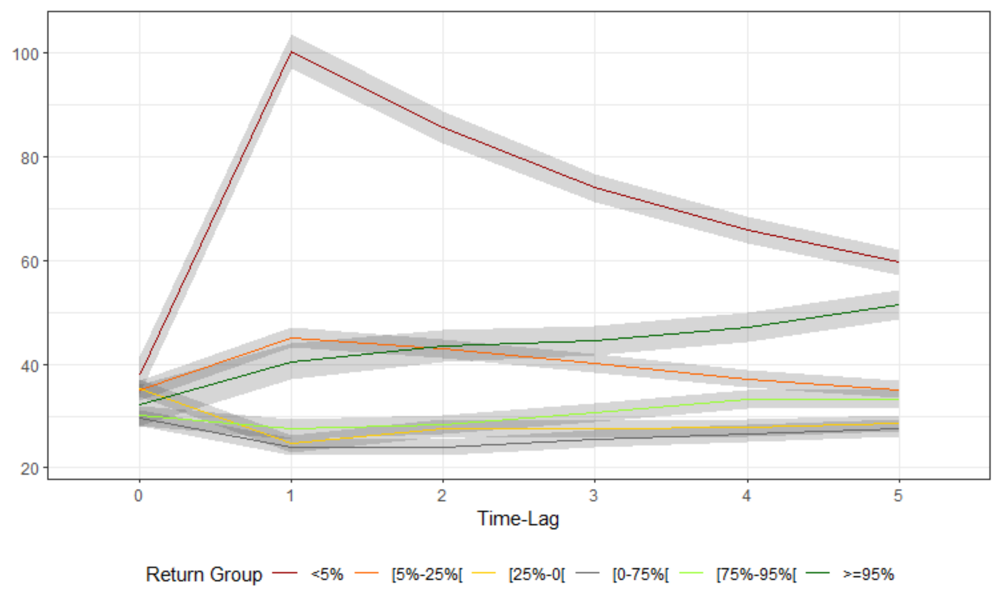
Panel C: Speed of Response to Extreme Negative Returns (*SpeedExtNeg*)

Energy	25.64^{***}	Health Care	2.64	Real Est.	-19.91
Materials	0.72	Financials	-2.25		
Industrials	-11.46^{*}	Inf. Tech.	-5.12		
Cons. Disc.	12.36^{*}	Com. services	-1.29		
Cons. Staples	-0.85	Utilities	-0.45		

Figure 1: The Impact of Overnight and Intraday Returns on RH Users' Trading Decisions
This table displays the $\hat{\beta}_g^{(L)}$ estimates obtained from the regressions in (4), with 95% confidence bands. The six regressions are all based on the complete sample of stock and day-time observations and are estimated by pooled OLS. Estimates are expressed in basis points. Panel A presents the results as a function of returns group level $\mathcal{G}_g$ while Panel B presents the results as a function of the time-lag L.



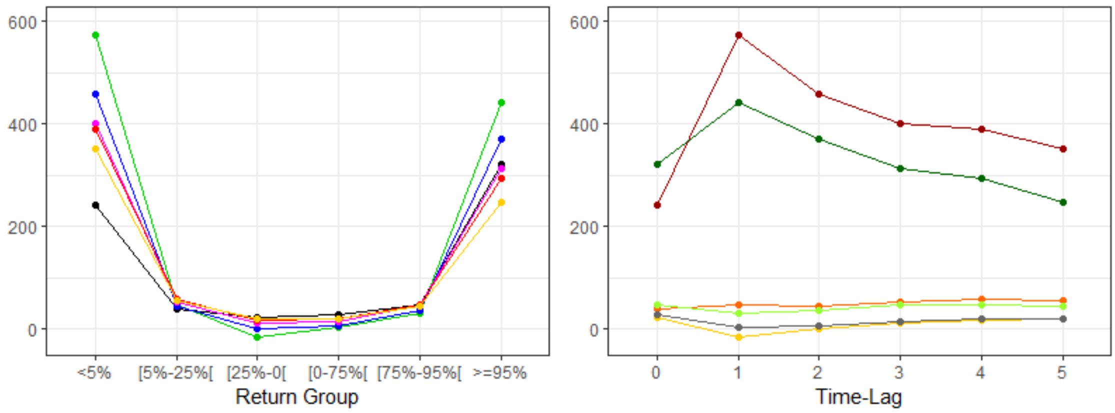
(a) By Return Group Level



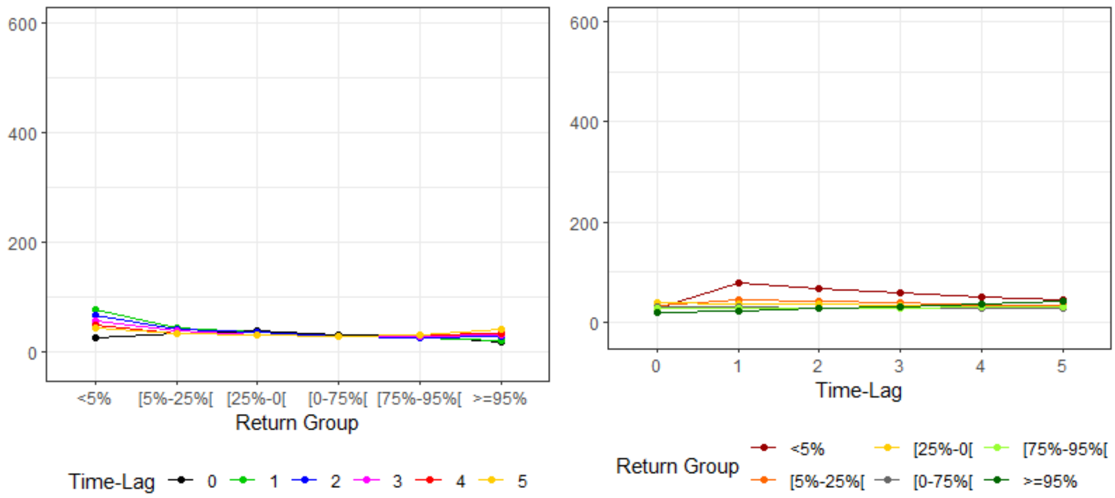
(b) By Time-Lag

Figure 2: Decomposing Key Behaviors by Type of Returns – Overnight vs. Intraday

This figure displays the $\hat{\beta}_{g,c}^{(L)}$ estimates obtained from the regressions in (6) using the type-of-return classification criterion. An overnight return is defined as a change between the last price observation of a given before the market closes and the first price observation of the next trading day after the market opens, expressed in daily units. An intraday return is defined as an hourly change between two consecutive prices of the same day, expressed in daily units. The six regressions are all based on the complete sample of stock and day-time observations and are estimated by pooled OLS. Estimates are expressed in basis points.

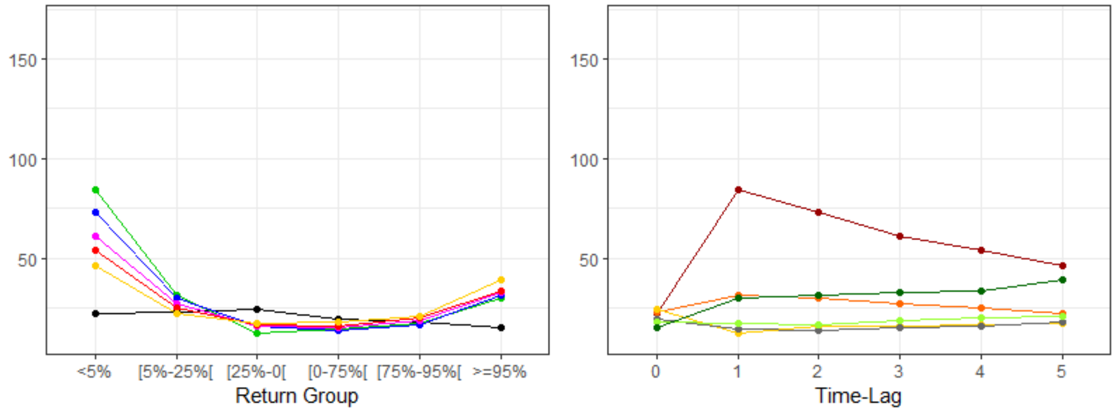


(a) Overnight Returns

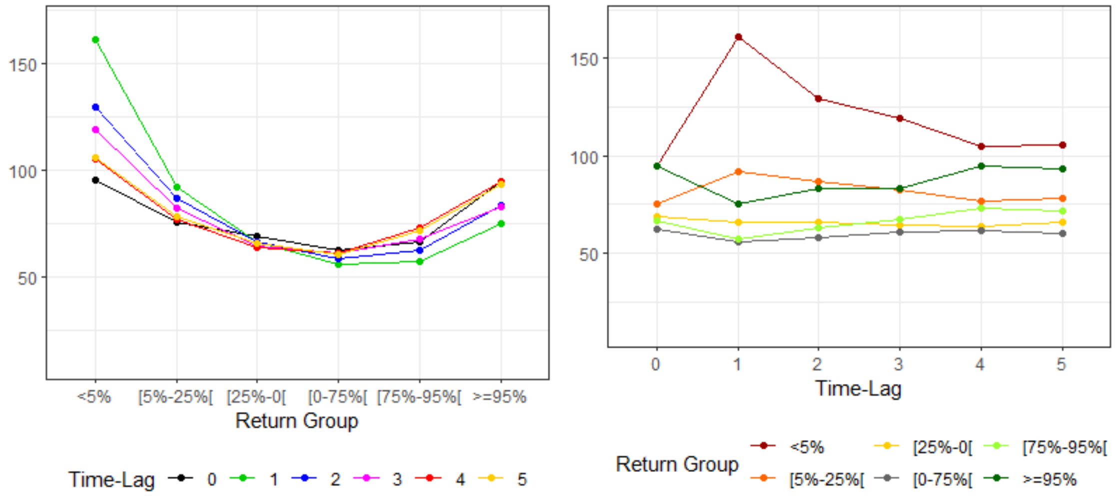


(b) Intraday Returns

Figure 3: Decomposing Key Behaviors Pre- and Post-COVID-19 Pandemic Announcement
This figure displays the $\hat{\beta}_{g,c}^{(L)}$ estimates obtained from the regressions in (6) using the pre- vs. post-COVID-19 pandemic announcement classification criterion, where the date of the announcement is March 11, 2020. The six regressions are all based on the complete sample of stock and day-time observations and are estimated by pooled OLS. Estimates are expressed in basis points.



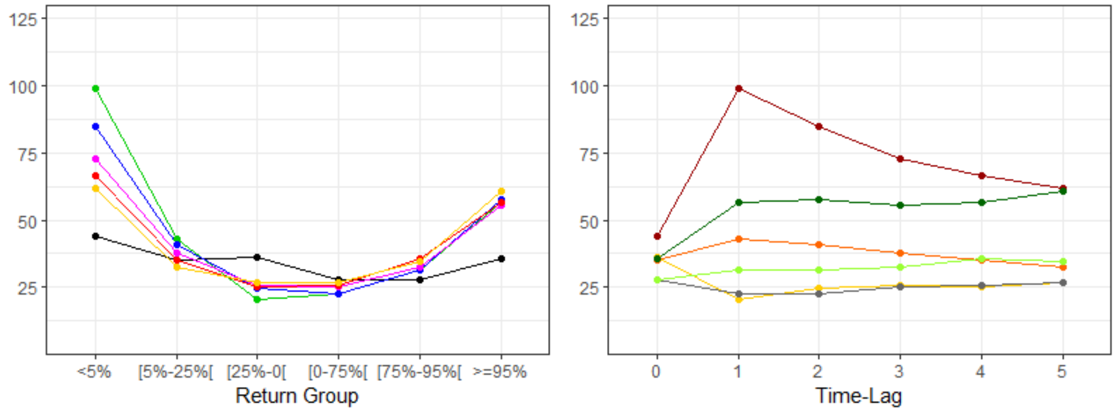
(a) Pre-COVID-19-Pandemic-Announcement Period



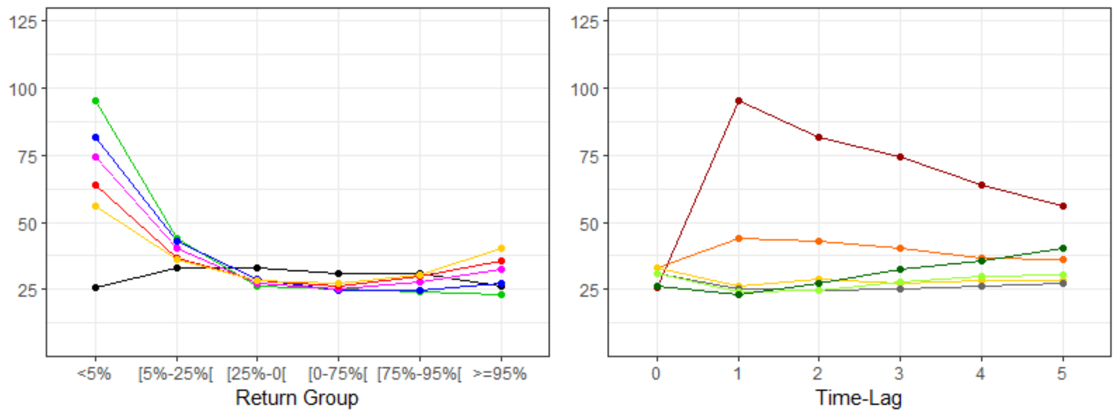
(b) Post-COVID-19-Pandemic-Announcement Period

Figure 4: Decomposing Key Behaviors by Company Size

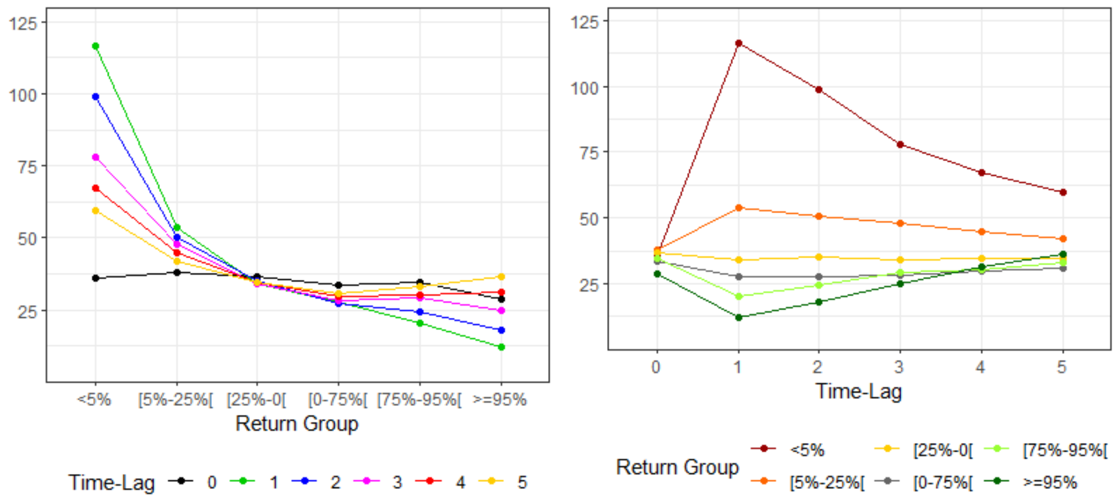
This figure displays the $\hat{\beta}^{(L)}_{g,c}$ estimates obtained from the regressions in (6) using the market capitalization classification criterion. The six regressions are all based on a sample of stocks and day-time observations and are estimated by pooled OLS. A subset of ten stocks was excluded from the original sample due to unavailability of data. Estimates are expressed in basis points.



(a) Small-cap stocks



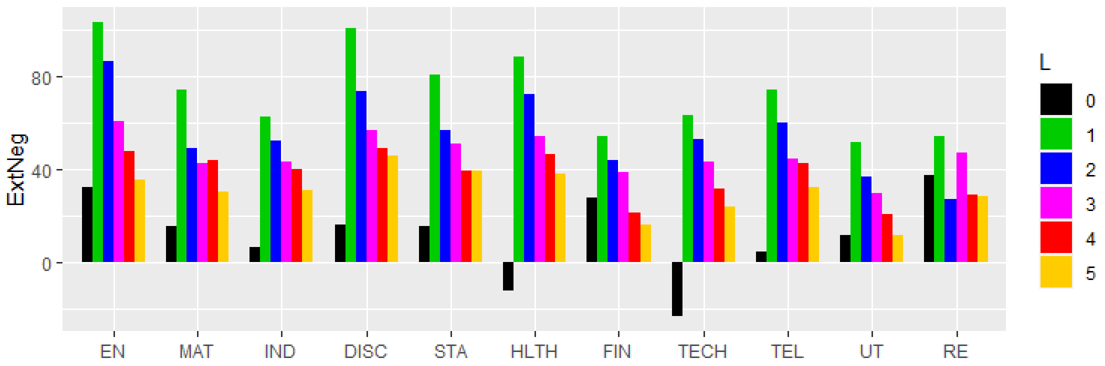
(b) Mid-cap stocks



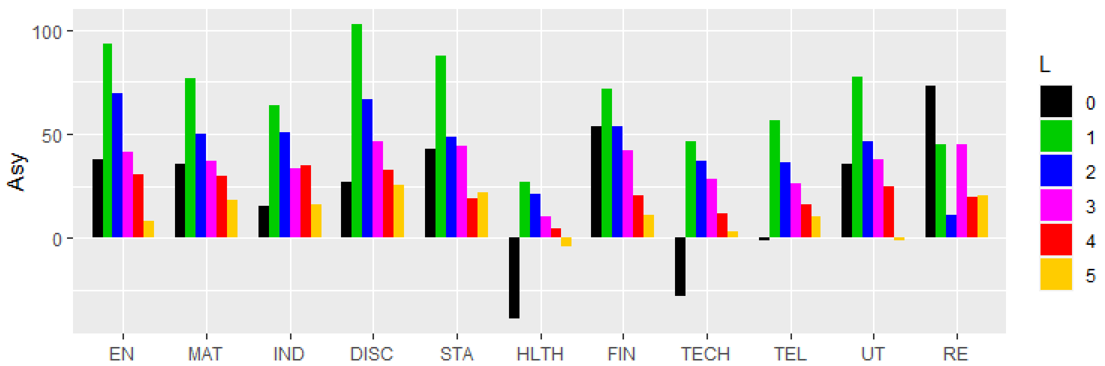
(c) Large-cap stocks

Figure 5: Decomposing Key Behaviors by Industry

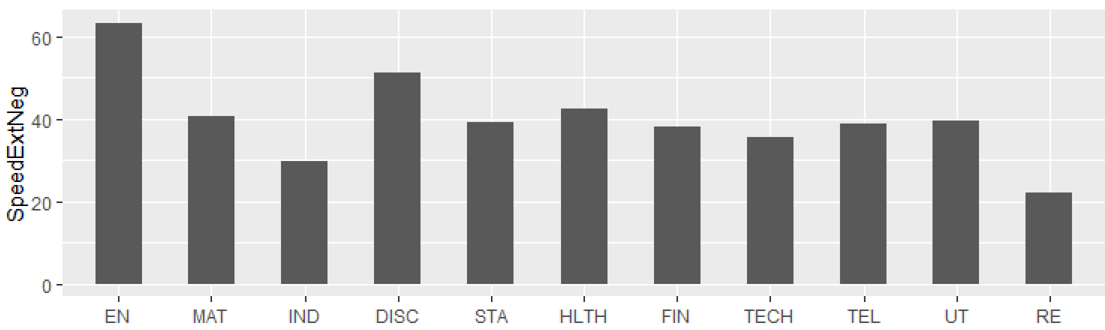
This figure shows our proxies representing each behavior for a given industry. The proxies have been computed according to the definitions in (7), using the $\hat{\beta}^{(L)}_{g,c}$ estimates of regressions (6) where the criterion is the industry and contains eleven levels ($C = 11$) that identify the sector as per the General Industrial Standard Classification (GICS). The six regressions are all based on a sample of stocks and day-time observations and are estimated by pooled OLS. A subset of 85 stocks was excluded from the original sample due to unavailability of data. Estimates are expressed in basis points.



(a) Response to Extreme Negative Returns (*ExtNeg*)



(b) Asymmetry of Response to Extreme Returns (*Asy*)



(c) Speed of Response to Extreme Negative Returns (*SpeedExtNeg*)