International Review of Financial Analysis 105 (2025) 104369

Contents lists available at ScienceDirect

International Review of Financial Analysis

journal homepage: www.elsevier.com/locate/irfa

Examining high-frequency patterns in Robinhood users' trading behavior

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ARTICLE INFO

JEL classification:
G11
G14
G40
G41
G53

Keywords:
Attention-induced trading
Robinhood
Retail investors
High-frequency data
Reaction speed
FinTech

ABSTRACT

Using intraday (hourly) and overnight changes in the number of Robinhood (RH) investors holding a stock, we examine their high-frequency trading behaviors in response to contemporaneous and lagged returns. RH investors do not react to *contemporaneous* returns. However, they respond to *lagged* intraday or overnight returns, exhibiting three high-frequency behaviors: (i) the number of RH investors increases more for stocks with *extreme* lagged returns than for those with *moderate* returns, suggesting attention-driven buying; (ii) this reaction is asymmetric, with larger increases in the number of RH users following extreme *negative* returns compared to extreme *positive* returns, suggesting that their contrarian buying is stronger than their momentum buying; (iii) this asymmetry is strongest immediately after extreme returns and dissipates over time. Compared to findings from daily data, our analysis shows that daily data underestimates this asymmetry. Further analyses reveal greater attention to overnight movements, exacerbated behaviors during COVID-19, and variation across firm sizes, with more contrarian buying for larger-cap firms.

1. Introduction

Retail participation in the stock market has increased significantly in recent years, with individual investors accounting for over 40% of total trades in the first quarter of 2021 in the United States. This trend is attributed to the rise of new FinTech commission-free trading platforms such as Robinhood (RH). These platforms made investing more accessible and attracted a new demographic of investors.[1]

While it is difficult to assess whether RH investors have influenced the behavior of larger retail traders, their impact on institutional investors — particularly hedge funds — has been well documented. The GameStop episode exemplifies this effect, as coordinated trading by RH investors created significant challenges for short-sellers, forcing institutional investors to adjust their risk management strategies in response to potential crowd-driven market movements. For example, Welch (2022, p.1490) writes: "(...) all short-sellers are now actively contemplating a world in which they could become exposed to such crowd risk at any moment".

This influx of new retail investors has also reshaped market dynamics. Among others, Eaton et al. (2022) analyze the effect of RH investors on financial markets using platform outages.[2] They find that market order imbalances and return volatility decrease and market liquidity increases for stocks with high retail interest when RH investors are absent from the financial markets due to RH outages. They argue that herding by inexperienced investors, such as RH investors, can create inventory risks and decrease liquidity in stocks with high retail interest, which in turn might have pricing implications. Policymakers could consider adjusting capital requirements or modifying market-making obligations for securities with high retail participation.

As the importance of this new type of investors in financial markets increases and poses challenges for regulators and market participants (*e.g.*, Fisch, 2022), a growing body of recent literature analyzes their trading behaviors. In particular, Barber et al. (2022), Fedyk (2024), Ülkü et al. (2023), and Welch (2022) analyze trading behaviors of RH investors at the *daily* frequency.[3]

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[1] See The Economist, "Just how mighty are active retail traders?," August 21, 2021, for a discussion about the rise of individual investors in the United States, while the profile of RH investors is discussed in Barber et al. (2022), Eaton et al. (2022), Jones et al. (2021), Van der Beck and Jaunin (2021), and Welch (2022) among others. The average age of RH investors is 31, and 50% are first-time investors. The average account size is $4000 compared to $127,000 or $234,000 for E-Trade and Charles Schwab, respectively.

[2] Jones et al. (2021) and Friedman and Zeng (2022) also exploit platform outages to measure retail investors' effects on financial markets.

[3] Other studies investigate Environmental, Social, and Governance (ESG) preferences of RH users (Moss et al., 2024), effects of COVID-19 on RH activity (Ozik et al., 2021) or sentiment-driven investing (Ben-David et al., 2022).

https://doi.org/10.1016/j.irfa.2025.104369
Received 9 August 2024; Received in revised form 23 April 2025; Accepted 30 May 2025
Available online 14 June 2025

However, recent studies show that this new type of retail investors adopt "a significantly higher trading frequency, but on smaller orders than those found for the clients of the other categories of intermediaries" (Chatillon et al., 2021) and have intensified intraday trading activities following high levels of Google searches (Meshcheryakov & Winters, 2022). In other words, this new type of retail investors tend to be more connected to markets than traditional retail investors and have easier and faster access to information, which allows them to react faster to new information. Furthermore, the features of the RH smartphone app, such as sending notifications, might make these investors more active throughout the day. Given these facts, we expect them to exhibit distinct trading behaviors at time intervals more granular than the daily frequency used in the existing literature.

In this paper, we fill this gap in the literature and analyze RH investors' high-frequency trading behaviors in reaction to intraday (hourly) and overnight contemporaneous and lagged returns. We focus on the reaction of RH investors to high-frequency returns for two reasons. First, this allows us to directly compare our intraday and overnight results to the daily results in Barber et al. (2022), Fedyk (2024), Ülkü et al. (2023), and Welch (2022). Second, these young and inexperienced investors are more likely to pay attention to returns, the simplest of the attention-grabbing events considered in Barber and Odean (2008).[4]

To obtain our results, we rely on two main data sources. First, we use the Robintrack data on the number of RH investors holding a specific stock at a particular time. The original database from Robintrack comprises over 140 million observations that are approximately one-hour spaced on more than 8000 distinct securities. Second, we obtain high-frequency transaction prices from the NYSE Trade and Quote (TAQ) Daily Product to compute hourly intraday and overnight returns, which we match to the Robintrack observations. After merging the two databases and keeping only common stocks, we obtain a panel of stock-day-time observations including over 2500 stocks from June 2018 to August 2020, resulting in more than seven million observations. In our main framework, we regress the change in the number of RH users holding a given stock on the corresponding contemporaneous and lagged intraday hourly or overnight volatility-adjusted returns grouped into percentile ranges while also controlling for a few other factors, including market return and its square. This allows us to analyze the propensity of RH investors to open new long positions after observing intraday hourly and overnight price movements of different signs and magnitudes.

We find that RH investors do not or cannot react to *contemporaneous* returns as the change in the number of RH investors holding a stock is not related to the stock's contemporaneous return.[5] On the other hand, they react to *lagged* intraday hourly or overnight returns and exhibit three high-frequency trading behaviors: First, the number of RH investors increases more for stocks with *extreme* lagged returns in the previous intraday or overnight period than for those with *moderate* lagged returns. In other words, RH investors exhibit both contrarian buying and momentum buying by opening new long positions in attention-grabbing stocks with extreme price movements. Second, this reaction to extreme lagged returns is asymmetric in the sense that the number of RH investors increases more following extreme *negative* returns compared to extreme *positive* returns. In other words, RH investors' contrarian buying behavior following extreme negative returns is more pronounced than their momentum buying behavior following extreme positive returns. Third, this asymmetry between their contrarian and momentum buying is much more pronounced for the first hour after observing the extreme return. It gradually decreases and disappears after several hours.

The first pattern, *i.e.*, the attention-driven buying, in RH investors' high-frequency trading behavior is similar to their daily trading behavior identified in the literature (see Barber et al., 2022; Fedyk, 2024; Ülkü et al., 2023; Welch, 2022). The second pattern, *i.e.*, the asymmetry between contrarian and momentum buying behaviors, is the main asymmetry we focus on and one of our main contributions in this paper as we show that it is much more pronounced at higher frequencies than daily. In fact, the literature based on daily data suggests either an asymmetry in the other direction (Welch, 2022), no asymmetry (Barber et al., 2022; Ülkü et al., 2023), or only a weak asymmetry in the same direction as our study (Fedyk, 2024). Welch (2022) finds that RH investors react to previous day's extreme price movements and that this effect is stronger for large stock price increases than for large price decreases. Barber et al. (2022) find that RH investors do not exhibit any asymmetry in their reaction on day t to either previous overnight (close on day $t-1$ to open on day t) or contemporaneous daily (close on day $t-1$ to close on day t) extreme returns since they tend to open new positions at the same rate for top gainers and losers.[6] Ülkü et al. (2023) analyze the trading behavior of retail/individual traders at the daily/weekly frequency using data from different countries as well as RH.[7] They find that retail investors in most of the countries in their sample exhibit strong daily/weekly contrarian trading behavior, with the important exception of RH investors, who might be different than traditional retail investors, as we argued above.[8] Finally, Fedyk (2024) documents that RH investors invest relatively more following extreme negative returns than after extreme positive returns. Consistent with this, we find a moderate asymmetry in their daily reactions and a much stronger asymmetry at higher frequencies. Our daily results align with earlier versions of Fedyk (2024), while the high-frequency findings highlight a more pronounced differential response to extreme return events.

The high-frequency nature of our analysis allows us to understand why we observe an asymmetric reaction to extreme negative versus positive returns at the hourly frequency but not at the daily frequency. Indeed, we find that this asymmetry tends to gradually decline over the hours, to almost completely disappear after five hours. More precisely, our results suggest a possible overreaction to extreme negative returns as RH investors open new long positions in past losers at a very high rate in the first hour, which then gradually declines in the following hours. On the other hand, RH investors possibly underreact to extreme positive returns as they open new long positions in the past winners at a relatively low rate in the first hour, which then gradually increases in the following hours. Since the reaction to extreme returns becomes almost symmetrical after five hours, this can explain why we do not observe this pattern at the daily level. Put differently, our results, while

[4] See also, Seasholes and Wu (2007) and Yuan (2015), for instance. Furthermore, understanding these finer temporal dynamics would provide deeper insights into the effects of these investors on financial markets.

[5] Given this result, any reaction we refer to in the rest of the paper is the reaction of RH investors to lagged and not contemporaneous returns.

[6] Barber et al. (2022, Section D.1) analyze the relation between the change in the number of RH investors holding a stock and the rank of this stock in top gainers (stocks with the highest positive returns) and top losers (stocks with the lowest negative returns). They "exclude the user change at the open on Robinhood to make the Robinhood user change more comparable with TAQ net retail buying" and then analyze the daily (open-to-close) reaction of RH investors to overnight (close-to-open) or daily (close-to-close) returns.

[7] Onishchenko and Ülkü (2022) also analyze the trading behavior of retail/individual traders at the daily frequency using data from the Korean stock exchange, instead of the RH platform. They find that retail investors exhibit a contrarian style, buying past losers and selling past winners, when trading large stocks. They also find that these retail investors are net buyers of winner stocks when trading smaller stocks. They argue that this finding is consistent with the attention-driven speculative buying discussed in Barber and Odean (2008) and write: "The small-cap segment, however, is dominated by individual investors, and the large number of smaller (difficult-to-analyse) stocks renders attention to a significant driver of individual investor behaviour".

[8] See Table 6 and the related discussion on pages 18–19 of their paper.

not refuting the current results based on daily data, suggest that the daily frequency is too coarse of a frequency to analyze the behavior of these ultra-connected investors.

Furthermore, the high-frequency framework allows us to identify the speed of RH investors' reaction to extreme returns, which is not possible using daily data. While RH investors do not or cannot react contemporaneously to extreme price movements as mentioned above, they react fast nonetheless. For example, we observe that most of the new long position openings in reaction to a large negative price movement occur within the first hour of observing this movement. Such a result cannot be captured using daily data.

Finally, our high-frequency analysis allows us to distinguish between two potential explanations for individual/retail investors' contrarian trading behavior. The first explanation is based on the use of limit orders by individual/retail investors, put forward by Linnainmaa (2010). Specifically, he argues that individual investors might appear contrarian due to their use of limit orders since, by definition, the stock price has to move against the price set in the limit order for it to execute. This explanation implies a negative contemporaneous relation between individual investors' net trading and daily returns. The second explanation is that individual investors react to past returns due to their inherent behavioral biases such as limited attention, disposition effect, or belief in mean reversion, which Onishchenko and Ülkü (2022) summarize as an uninformed attempt at buying low and selling high based on recent prices as heuristic reference points. Our high-frequency results favor the second explanation, at least for RH investors, since we find that they exhibit a strong contrarian buying behavior in response to lagged, but not contemporaneous, extreme negative returns.[9]

We also contribute to the literature by investigating how these behaviors vary depending on the type of price movement, company size, and before and after COVID-19. Motivated by previous studies such as Berkman et al. (2012), Jones et al. (2022) and Lou et al. (2019), we start our analysis by distinguishing between intraday hourly and overnight price movements. Berkman et al. (2012) show that "high-attention stocks have high levels of net retail buying at the start of the trading day". Lou et al. (2019) argue that there exists an "intraday clientele" and an "overnight clientele". Jones et al. (2022) examine morning order imbalances in relation to previous day-time (close-to-open) and overnight returns. We find that RH investors' behaviors described above are much more pronounced for overnight returns. The inclination of RH investors to open more new positions in stocks that exhibit extreme returns is approximately thirty times larger when this large movement occurs overnight as opposed to during trading hours. In addition, the asymmetry of response is stronger after an overnight movement compared to an intraday movement, indicating that RH investors tend to open more (fewer) new positions in overnight (intraday) big losers relative to overnight (intraday) big gainers. Finally, the fast reaction to large negative movements is also more pronounced for overnight returns. Hence, RH investors are faster at opening new positions in stocks that exhibit large negative overnight movements compared to those that exhibit such movements during trading hours.

We then focus on the effect of the COVID-19 pandemic on RH investors' intraday trading behaviors. Consistent with the findings of Ozik et al. (2021) and Ülkü et al. (2023), we observe that RH investors' buying activity increased in the post-COVID period. Our results also show that, in the six months following the announcement of the global pandemic, RH investors' buying behavior towards extreme movers intensified, and their reaction speed to large downward movements also increased.

[9] As we will discuss in further detail in Section 2.1, the original time provided by Robintrack indicates when data were retrieved from the RH platform. However, there is a delay of approximately 45 min between the actual observation time and retrieval time. Our robustness checks show that this conclusion is robust to using 30- and 60 min delays instead of the 45 min delay used for our main results.

We also find important variations in the trading attitudes of RH investors across the firm size. RH investors tend to purchase both big losers and gainers within the small-cap segment. For large-caps, their behavior leans more towards a predominantly contrarian buying approach, as they primarily focus on buying the big losers. Stated differently, the asymmetry between their contrarian and momentum buying behaviors following extreme returns is significantly more pronounced for larger firms, which confirms Onishchenko and Ülkü (2022) finding on daily Korean data. They also exhibit a faster reaction to large negative movements of large-cap stocks compared to small-cap stocks. At the daily level, Fedyk (2024) also highlights the propensity of RH investors to invest in large stocks that have experienced a negative extreme return but does not find this effect for small-cap stocks. Previous research studying behavioral trading patterns of retail investors in relation to firm size has highlighted the presence of stronger herding behavior among individual investors for small stocks (*e.g.*, Hsieh et al., 2020; Venezia et al., 2011). Other studies have shown that individuals have a comparative advantage in trading small-cap stocks (*e.g.*, Jirajaroenying et al., 2019; Kelley & Tetlock, 2013). Expanding upon this literature, our study contributes new insights into the impact of firm size on the key high-frequency trading behaviors exhibited by RH investors.

The paper is organized as follows. Section 2 presents the data and the variables used in our analyses. Section 3 introduces the methodology and discusses the main empirical findings. Section 4 presents the conditional analyses of RH users' behaviors. Section 5 discusses robustness tests, and Section 6 concludes.

2. Data and variable definitions

2.1. Data

From May 2018 to August 2020, Robintrack relied on Robinhood's API to collect data on the number of investors holding a specific stock at a specific time and then shared this information publicly through their website www.robintrack.net. Following Barber et al. (2022) and Welch (2022), we use this data to proxy for RH investors' trading behavior—in particular, Barber et al. (2022) provide empirical evidence that the change in the number of RH users holding a stock is positively related with the net buying (order imbalance) for that stock computed using Trade and Quote (TAQ) data set. Compared to these studies, however, we consider intraday and overnight observations rather than daily observations. 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. Our notation highlights the fact that the time stamp is specific to each stock.

The original time provided by Robintrack indicates when data were retrieved from the RH platform. However, as mentioned in Barber et al. (2022) and confirmed by our discussions with the administrator of Robintrack, Casey Primovic, there is a delay of approximately 45 min between the actual observation time and retrieval time. For instance, a data point with an original time of 10.45 am represents a snapshot of the data at approximately 10 am. To ensure accuracy and work with observation times, we thus subtract 45 min from all timestamps $t_i(k)$.[10]

For price data, we use high-frequency transaction prices from the NYSE Trade and Quote (TAQ) Daily Product. We match all RH users' holdings observations $N_{i,t_i(k)}$ to the last trade price available of stock i

[10] This delay is due to the frequency at which RH updated user count information and made it available to retrieve from its API. Our best guess is that RH had periodic jobs running that aggregated the total user holding counts every x minutes, with x representing the frequency at which these jobs ran. According to our discussion with Casey Primovic, x is likely between 30 and 60 min. As robustness tests, we consider alternative delays of 30 and 60 min. Our conclusions remain valid under these assumptions. For more details, see the online appendix.

before time $t_i(k)$. Similarly, 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.[11]

The original database from Robintrack comprises over 140 million observations that are approximately one-hour spaced on more than 8000 securities. To ensure data quality, we apply several adjustments. We follow Welch (2022) and drop the first month of the original period. We focus on observations during market-opening hours to match RH users' holdings and trade prices (9.30 am – 4 pm). We only consider common stocks (CRSP share codes of 10 or 11). We identify and remove dual-class tickers that are not named correctly in the Robintrack datasets and adjust for repeated intra-hour observations. A detailed list of our adjustments is provided in the online appendix. Our final sample contains over 7.5 million observations on 2583 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, which we refer to as "position openings", is a proxy for the aggregate trading behavior of RH users concerning a given stock. A positive value means that more RH users have opened new positions than closed existing positions in the stock. Formally, it is defined as

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

An intraday change is approximately a one-hour change between two consecutive 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 intraday and overnight 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, $SF_{INT} = \frac{60}{MNT(t_i(k-1),t_i(k))} \times 6.5 \times 2$. 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 day-time" (from open to close time) change as the market is open during 6.5 h. The last term converts this total day-time change into a full-day change. Similarly, in the bottom equation, $SF_{OV} = 2$ converts the overnight change into a full-day change. The scaling factor is essential in bringing our intraday and daily results to the same scale. To be more precise, the variable of interest in our intraday analysis, before scaling, is the change in the number of positions in a given stock between the two observations from the Robintrack dataset. The average time between the two observations is about one hour, implying that our variable of interest can be considered the hourly change in the number of positions. We cannot simply compare an hourly rate position openings (or closings) to a daily rate without any normalization.

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 in (1), 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 returns (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 the five-minute ticks subsampling realized volatility estimator developed by Zhang et al. (2005). Subsampling at the five-minute frequency makes consensus in the literature (*e.g.*, Liu et al., 2015). For overnight returns, we employ a GJR-GARCH(1,1) estimator (Glosten et al., 1993) computed on the series of stock i overnight returns. To be consistent with the non-standardized returns $R_{i,t_i(k)}$ expressed in daily terms, we convert these two volatility estimators to a full-day scale as well, using the multiplying factor $\sqrt{2}$. 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:

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

There are cross-sectional and time-series reasons for using standardized returns instead of raw returns. As defined later in this section, our extreme return bins are based on our panel data set, which includes high- and low-volatility stocks and volatile and tranquil periods. From a cross-sectional perspective, if we do not standardize returns and instead use raw returns, high-volatility stocks will be overrepresented in our extreme return observations. This, in turn, creates a sample-selection bias, and our results will be based primarily on small stocks with significant volatilities. Similarly, from a time-series perspective, if we do not standardize returns and instead use raw returns, our observations with extreme returns will be from periods with high volatility. Combined, these cross-sectional and time-series effects imply that our results will be biased towards high-volatility stocks in volatile periods if we use raw instead of normalized returns.

Table 1 presents summary statistics on our main variables. These statistics are computed over the complete sample of stock and day-time observations. Panel A shows that the number of open positions increases on average by 9.37 per day. 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. However, the median change is zero as an important number of observations remain unchanged over an hour or overnight. Comparing intraday and overnight activities reveals that, while the respective averages are relatively close at approximately 9 and 12, RH users' trading behavior tends to be more dispersed within the day than overnight. Panel B reports results for 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, but its 5th and 95th percentiles suggest wider tails.[12]

Since we aim to differentiate the trading behaviors of RH investors in response to movements of different magnitudes — notably the extreme negative 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 percentile cutoffs are formed using all standardized return observations, that is, all stock and day-time observations. To define a clear separation between negative

[11] To minimize the effect of micro-structure issues on our extraction of transaction prices from TAQ, we apply filters following Barndorff-Nielsen et al. (2009). In particular, we retain transactions originating from NYSE, NASDAQ, and AMEX only.

[12] Note that approximately 85% (15%) of the total number of observations correspond to intraday (overnight) changes or returns, as a given stock generally counts one overnight and six hourly-spaced intraday observations per day.

Table 1
Summary statistics of main variables.

Panel A: Position openings $\Delta N_{i,t_i(k)}$										
	Av	Std	5th	25th	50th	75th	95th	$Nobs$	T	#
Intraday	8.91	120.51	−64.07	−12.98	0.00	12.96	77.96	6,584,095	527	2,583
Overnight	11.89	102.89	−18.00	−2.00	0.00	4.00	48.00	1,201,860	526	2,583
All	9.37	117.97	−52.01	−4.00	0.00	6.00	68.00	7,785,955	527	2,583
Panel B: Standardized returns $r_{i,t_i(k)}$										
	Av	Std	5th	25th	50th	75th	95th	$Nobs$	T	#
Intraday	−0.02	3.22	−5.38	−1.90	0.00	1.88	5.27	6,584,095	527	2,583
Overnight	0.02	4.26	−3.04	−0.89	0.02	0.98	3.02	1,201,860	526	2,583
All	−0.02	3.40	−5.14	−1.69	0.00	1.69	5.03	7,785,955	527	2,583

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 0.5th and 99.5th percentiles. 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.

Table 2
Classification of standardized returns.

Panel A: Group definitions						
	$\mathcal{G}_1$	$\mathcal{G}_2$	$\mathcal{G}_3$	$\mathcal{G}_4$	$\mathcal{G}_5$	$\mathcal{G}_6$
PRCT	<5%	[5%–25%[	[25%–0[	[0-75%[	[75%–95%[	≥95%
$r_{i,t_i(k)}$	< -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	371,551	1,415,607	1,321,793	1,698,224	1,404,641	372,279
Overnight	17,747	141,584	415,282	457,678	152,550	17,019
All	389,298	1,557,191	1,737,075	2,155,902	1,557,191	389,298

Panel A shows the breakdown of the groups by percentile cutoffs (PRCT) and their corresponding quantile values ($r_{i,t_i(k)}$). 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.

and positive returns, groups $\mathcal{G}_3$ and $\mathcal{G}_4$ are based on a "hard cutoff" corresponding to a zero return. 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 details this classification by groups. $\mathcal{G}_1$ contains the most extreme negative standardized returns that are below −5.14. By construction, it corresponds to 5% of all observations or 389,298 returns. Among these observations, 371,551 are intraday returns, and 17,747 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.

3. The reaction of RH investors to high-frequency price movements

This section presents our main empirical results analyzing how RH investors respond to intraday hourly and overnight price movements. To this end, we first present the methodological framework. We then discuss the three key behaviors RH investors exhibit in response to lagged returns.

3.1. Methodological framework

We aim to assess how our proxy for RH investor's trading behavior, the RH users' position openings $\Delta N_{i,t_i(k)}$, changes as a function of past intraday hourly and overnight standardized returns $r_{i,t_i(k-L)}$ categorized into groups $\mathcal{G}_g$ defined above. Formally, we estimate the following 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 $L = 0, \dots, 5$. L defines the time-lag(s), or number of time-step(s), between the intraday or overnight return and the position openings. $I_{\mathcal{G}_g}(r_{i,t_i(k-L)})$ is an indicator function that is equal to one if $r_{i,t_i(k-L)} \in \mathcal{G}_g$ and zero otherwise. We consider the contemporaneous relationship ($L = 0$), and the lagged relationships up to five time-lags ($L = 1, \dots, 5$). Recall that the index k tracks the number of observations for stock i. In other words, for a given stock i, we create a time series dataset by consecutively stacking intraday and overnight observations. This, in turn, implies that $r_{i,t_i(k-L)}$ can correspond to an intraday return from the same trading day, an overnight return, or an intraday return from the previous trading day.[13] We are interested in the estimates of $\beta_g^{(L)}$, which measure the propensity of RH users to open new positions, after L time-step(s), in stocks experiencing price movements of different magnitudes—from extremely negative to extremely positive. Our controls, $\mathrm{CTRL}_{i,t_i(k)}^{(L)}$, include two groups of variables: (i) stock i's contemporaneous and lagged (up to five) returns and their squares except the return corresponding to the time-lag of interest, that is, $r_{i,t_i(k-j)}$ and $r^2_{i,t_i(k-j)}$ ($j = 0, 1, \dots, 5; j \neq L$); and (ii) contemporaneous and lagged (up to five) market returns and their squares, that is, $r_{M,t_i(k-j)}$ and $r^2_{M,t_i(k-j)}$ ($j = 0, 1, \dots, 5$). To facilitate the interpretation of the coefficients of interest, we employ demeaned control variables.

In all six specifications presented in (4), the dependent variable $\Delta N_{i,t_i(k)}$ and the second group of control variables (market returns) remain unchanged. The elements that vary as we consider different L are the lagged stock return categorical variables $I_{\mathcal{G}_g}(r_{i,t_i(k-L)})$ and the first group of controls accounting for the other lagged stock returns, that is, $r_{i,t_i(k-j)}$ and $r^2_{i,t_i(k-j)}$ ($j = 0, 1, \dots, 5; j \neq L$). For example, in the

[13] For example, let us assume a timestamp $t_i(k)$ corresponding to *2018-11-14, 13:45*. It means that $\Delta N_{i,t_i(k)}$ measures the change between 12:45 and 13:45. The contemporaneous lag return ($L = 0$) is an intraday return between 12:45 and 13:45. The first lag return ($L = 1$) is an intraday return between 11:45 and 12:45. The second lag return ($L = 2$) is an intraday return between 10:45 and 11:45. The third lag return ($L = 3$) is an intraday return between 9:45 and 10:45. The fourth lag return ($L = 4$) is an overnight return between the last observation of the previous trading day (say 15:45) and the first observation of the current trading day, 9:45. The fifth lag return ($L = 5$) is an intraday return between 14:45 and 15:45 on the previous trading day.

Table 3
Reaction of RH investors to intraday hourly and overnight price movements.

	Time-Lag L					
	0	1	2	3	4	5
<5%	8.49	21.17	18.02	15.71	13.90	12.86
	(12.85)	(20.16)	(19.31)	(19.02)	(18.36)	(17.94)
[5%–25%[	9.41	12.36	11.85	10.95	10.30	10.00
	(13.81)	(15.40)	(15.26)	(14.93)	(14.58)	(14.19)
[25%–0[	9.80	8.21	8.63	8.76	8.56	8.58
	(14.63)	(12.54)	(13.28)	(13.47)	(13.40)	(13.54)
[0–75%[	8.50	7.04	7.23	7.60	7.86	7.89
	(14.12)	(12.42)	(12.55)	(13.03)	(13.47)	(13.64)
[75%–95%[	9.91	8.07	8.41	9.04	9.86	10.12
	(14.75)	(14.06)	(14.51)	(14.80)	(15.31)	(15.52)
≥95%	10.38	8.46	9.28	10.10	10.66	11.60
	(16.75)	(16.71)	(18.18)	(18.39)	(18.92)	(19.91)
$Adj.R^2$	0.001	0.001	0.001	0.001	0.001	0.001
$Nobs$	7,773,040	7,773,040	7,773,040	7,773,040	7,773,040	7,773,040

This table reports the $\hat{\beta}_g^{(L)}$ estimates obtained from regressions (4). The six regressions are based on the complete sample of stock and day-time observations and are estimated by pooled OLS. Associated t-statistics are shown in parenthesis. The standard errors are clustered at the stock level and corrected for heteroskedasticity.

first specification with $L = 0$, we evaluate the relationship between RH users' position openings and contemporaneous returns, controlling for the stock-specific returns at lags $L = 1, \ldots, 5$. Similarly, in the second specification with $L = 1$, we evaluate the relationship between RH users' position openings and returns over the last hour or the last overnight period (one time-lag), controlling for stock-specific returns at lags $L = 0, 2, \ldots, 5$.[14]

We estimate each specification based on the complete panel of stock-day-time observations, and compute standard errors clustered at the stock level and corrected for heteroskedasticity (*e.g.*, Petersen, 2009). Note that the specifications reported here represent pooled OLS models. As robustness tests, we also estimate panel regressions with firm and date-time fixed effects. Our fixed effects results, reported in Section 3 of the online appendix, remain quantitatively and qualitatively similar.

3.2. Three key behaviors by RH investors

Table 3 presents the estimates for all specifications, which are also summarized visually in Fig. 1. The table and the figure present the propensity of RH users to open new long positions in reaction to contemporaneous and lagged returns of various magnitudes.

Our results for contemporaneous returns (*i.e.*, $L = 0$) show that the change in the number of RH investors holding a stock is not related to the stock's contemporaneous return. In other words, RH investors do not or cannot seem to react to contemporaneous returns. On the other hand, our results indicate that the relation between RH investors' position openings and intraday hourly or overnight returns becomes statistically and economically significant after approximately one hour. In particular, we observe the following three high-frequency trading behaviors.

Behavior #1: The increase in the number of RH investors is similar for stocks with extreme lagged returns in the previous intraday or overnight period than for those with moderate lagged returns.

Panel A of Fig. 1 shows that the change in the new position openings exhibits a smirk as a function of past returns for all lags (*i.e.*, $L = 1, 2, \ldots, 5$). RH users open more positions in stocks that experience extreme (intraday hourly or overnight) price movements than in stocks that did not experience such extreme movements. For example, the average change in the number of RH investors holding a stock one period after an extreme negative or positive return is about 14.82 (= $(21.17 + 8.46)/2$) per day. This is approximately two times higher than the average change of 7.63 (= $(8.21 + 7.04)/2$) investors per day following a moderate return between the 25th and 75th quantiles. We are not the first to report such behavior by RH investors. Using daily data, Barber et al. (2022), Fedyk (2024), and Welch (2022) also find that RH investors react more strongly to extreme price movements. This is also related to the attention-driven buying by individual/retail traders discussed in Barber and Odean (2008) and Onishchenko and Ülkü (2022), among others. Our results show that RH investors also exhibit high-frequency attention-driven buying in response to lagged extreme returns, the simplest of all attention-grabbing events considered in Barber and Odean (2008).

Behavior #2: This reaction to extreme lagged returns is asymmetric in the sense that the number of RH investors increases more in the period immediately following extreme negative returns compared to extreme positive returns.

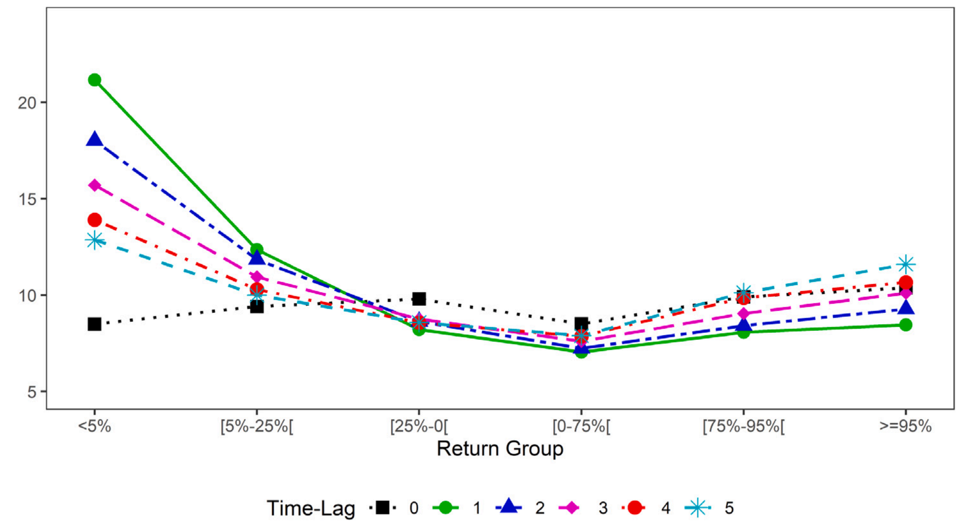
An important characteristic of the first behavior identified above is that RH users do not respond similarly to lagged extreme negative and positive returns. In other words, RH investors open, on average, more positions in stocks that experienced extreme negative returns (the big losers) than in those that experienced extreme positive returns (the big gainers). To illustrate this, consider the reaction of RH investors again after a one-time period. The increase in RH investors holding stock after a large negative return (21.17 per day) is about two and a half times higher than after a large positive return (8.46 per day). Furthermore, the magnitude of this asymmetry decreases as we consider RH investors' reactions to return realizations that happened further in the past. For example, the increase in the number of RH investors holding a stock is similar five periods after observing a large negative or positive return (12.86 and 11.60, respectively).

Behavior #3: RH investors are particularly fast at opening positions in stocks that exhibit large negative price movements.

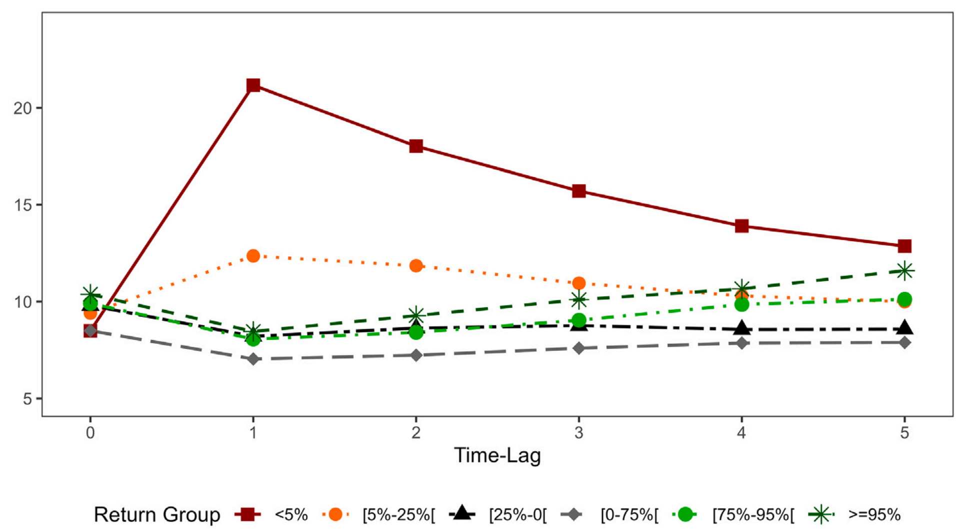
Panel B of Fig. 1 presents the reaction of RH investors to different returns as a function of time-lag, allowing us to assess their reaction speed. First, we focus on their reaction speed to extreme negative returns (below the 5th percentile). As previously mentioned, the response of RH investors to contemporaneous returns appears relatively muted, as indicated by the position openings, which are not significantly different from the overall average across different return groups. However, after one period, the change in RH investors holding a stock is at its highest at 21.17 accounts per day. It then monotonically decreases with further time-lags, reaching a rate of 12.86 accounts per day after five periods. This suggests that the reaction speed to extreme negative price movements is high. Specifically, most RH users acquire these stocks during approximately the one-hour or overnight period following the realization of this large negative price movement. We observe a similar pattern, albeit to a lesser extent, for stocks in the second most negative return group (between the 5th and 25th percentile). These results suggest that RH investors might overreact to extreme negative price movements.

Second, RH investors do not exhibit such a high reaction speed to returns higher than the 25th percentile. If anything, our results suggest that RH investors tend to underreact to lagged extreme positive price movements. Specifically, they open positions at a rate of about 8.46 accounts per day approximately one hour after observing an extreme positive return, and this rate slowly but monotonically increases to about 11.60 accounts per day after five periods. Finally, their reaction to moderate returns (between the 25th and 75th percentile) does not appear to depend closely on the time-lag.

[14] These six separate specifications should not be viewed as independent but rather like a system since we include stock-specific returns at different lags except the one in question as control variables in each of the six specifications. Moreover, we emphasize that we cannot estimate them as a single equation even if we drop controls. This is because certain stocks belong to a given group for several lags, which leads to multicollinearity problems.



(a) By Return Group Level



(b) By Time-Lag

Fig. 1. Reaction of RH investors to intraday hourly and overnight price movements
This figure displays the $\hat{\beta}_g^{(L)}$ estimates obtained from regressions (4). The six regressions are based on the complete sample of stock and day-time observations and are estimated by pooled OLS. Estimates are expressed in basis points. The top plot presents the results as a function of returns group level $\mathcal{G}_g$ while the bottom plot presents the results as a function of the time-lag L.

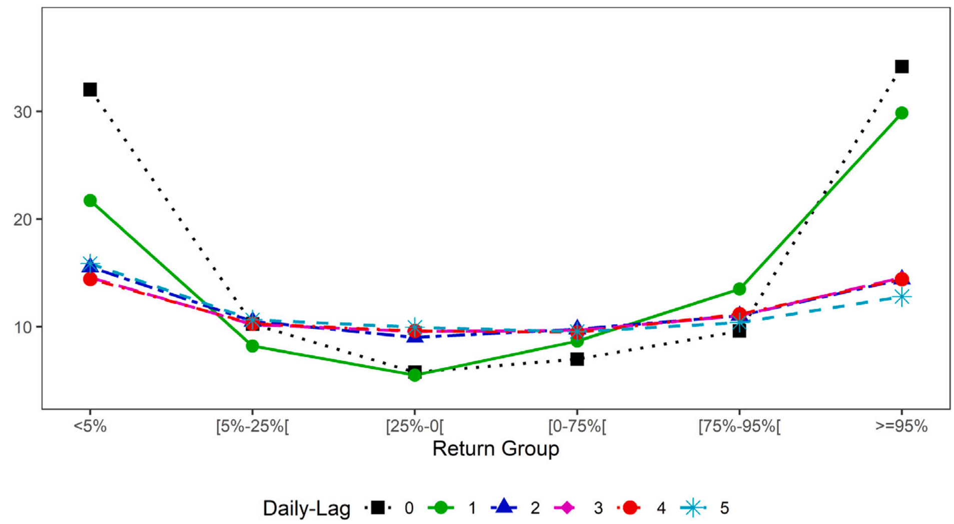
3.3. Comparison of Robinhood investors' high-frequency and daily trading behaviors

In this section, we analyze the similarities and differences between RH investors' high-frequency (intraday and overnight) and daily trading behaviors, based on (i) our own daily analysis and (ii) daily analysis in the existing literature.

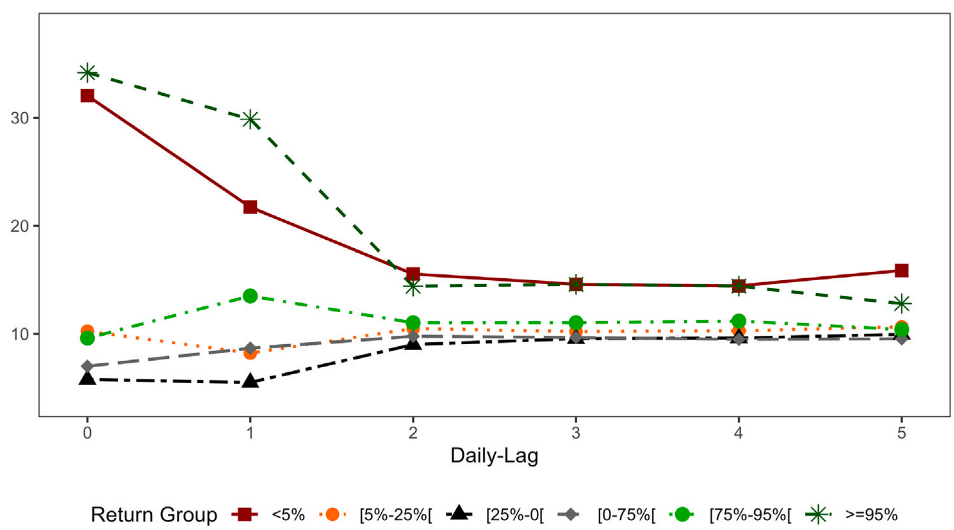
3.3.1. Robinhood investors' daily trading behaviors in our empirical framework

We start with the comparison based on our own daily analysis. That is, we estimate the same models presented in (4) where the time-steps $t_i(k)$ now account for days. To construct the daily change in the RH investors holding a stock, we identify the last available observation before 4 pm (the "close" observation) and construct a daily ("close-to-close") series of RH users' position openings. For the main independent variables we compute close-to-close returns standardized by their daily volatility estimated with a GJR-GARCH(1,1) model. We refer to the online appendix for more detail on our daily-frequency methodology.

Fig. 2 and Table 4 present these daily-frequency results. Our findings for the RH investors' daily trading behavior can be summarized as follows: First, the reaction of RH investors to daily extreme returns lasts for approximately two days—the day the extreme return is observed and the following day. Beyond the first two days, the RH investors' reaction to extreme returns decreases significantly and remains at the same level for further lags, still slightly higher than their reaction to more moderate returns. Second, RH investors do not exhibit much asymmetry in their response to contemporaneous extreme negative versus positive returns at the daily frequency (32.04 per day on days with negative extreme returns versus 34.17 on days with positive extreme returns). That said, they seem to exhibit an asymmetric reaction the following day. Specifically, RH investors open more new accounts on the following day after observing extreme positive returns than extreme negative ones (29.86 vs. 21.73). These daily results show the



(a) By Return Group Level



(b) By Daily-Lag

Fig. 2. Reaction of RH investors to price movements at daily frequency
This figure displays the $\hat{\beta}_g^{(L)}$ estimates obtained from daily-frequency regressions equivalent to high-frequency regressions presented in (4). The six regressions are based on the complete sample of stock-day observations and are estimated by pooled OLS. Estimates are expressed in basis points. The top plot presents the results as a function of returns group level $\mathcal{G}_g$ while the bottom plot presents the results as a function of the daily-lag L.

importance of a higher-frequency analysis as RH investors seem to exhibit different trading behaviors at the daily frequency than at the intraday frequency, which we discuss next.

Turning our attention to comparing our daily frequency results just presented above to our higher-frequency results (Fig. 1 and Table 3) reveals very interesting facts. Note that the results from both frequencies can be directly compared, given that estimates in both analyses are expressed in daily terms.

First, regarding behavior #1, the increase in the number of RH users in the first high-frequency period (*i.e.*, $L = 1$: the time-step is either an intraday one-hour period or an overnight period) following extreme negative returns is about 21.17 per day. This increase in response to an extreme contemporaneous daily negative return (*i.e.*, daily lag $L = 0$: the 24-h period corresponding to close-to-close observations) is about 32.04 per day. This suggests that about two-thirds of the daily reaction to extreme negative returns happens during the first one-hour intraday period or overnight period after observing the return. Again, this highlights that taking a higher-frequency perspective brings valuable new information. Second and perhaps more importantly, the asymmetry in RH investors' reactions to extreme negative and positive returns (behavior #2) is much more pronounced at the high-frequency level. Specifically, considering the one-time step ($L = 1$) again, our high-frequency results show that the increase in RH investors after a large negative movement is about 12.71 per day, which is higher than after a large positive movement. This asymmetry in their high-frequency reaction is in the opposite direction and almost six times the asymmetry in their daily reaction (*i.e.*, $-2.13 = (32.04 - 34.17)$). Therefore, a daily analysis would significantly underestimate the asymmetry in RH investors' response to extreme positive and negative returns. Here again, looking at this specific behavior with a high-frequency lens seems to tell a different story than with a daily lens. Finally, our high-frequency results demonstrate that RH investors are particularly quick to react to extreme negative returns while slower to react to extreme

Table 4
Reaction of RH investors to price movements at daily frequency.

	Daily-Lag L					
	0	1	2	3	4	5
<5%	32.04	21.73	15.54	14.58	14.44	15.87
	(22.14)	(17.75)	(14.45)	(14.59)	(14.45)	(15.06)
[5%-25%[	10.26	8.22	10.50	10.21	10.29	10.65
	(12.44)	(12.32)	(14.19)	(14.62)	(14.48)	(14.62)
[25%–0[	5.79	5.51	9.02	9.56	9.62	9.96
	(10.09)	(11.92)	(15.75)	(15.88)	(15.76)	(16.25)
[0–75%[	7.00	8.67	9.79	9.67	9.50	9.55
	(11.79)	(13.70)	(15.60)	(15.20)	(15.12)	(15.54)
[75%–95%[	9.61	13.51	11.03	11.03	11.19	10.40
	(14.05)	(16.05)	(15.74)	(15.41)	(15.71)	(14.91)
≥95%	34.17	29.86	14.41	14.58	14.42	12.80
	(23.47)	(20.51)	(13.91)	(14.49)	(14.35)	(13.42)
$Adj.R^2$	0.011	0.013	0.012	0.011	0.011	0.011
$Nobs$	1,188,945	1,188,945	1,188,945	1,188,945	1,188,945	1,188,945

This table reports the $\hat{\beta}_g^{(L)}$ estimates obtained from daily-frequency regressions equivalent to high-frequency regressions presented in (4). The six regressions are based on the complete sample of stock-day observations and are estimated by pooled OLS. Associated t-statistics are shown in parenthesis. The standard errors are clustered at the stock level and corrected for heteroskedasticity. For more details on the construction of these regressions, we refer to Section II of the online appendix.

positive returns. On the other hand, any daily analysis is, by definition, silent on the intraday reaction speed of RH investors to returns.

3.3.2. Robinhood investors' daily trading behaviors in the literature

We now compare our high-frequency and daily results with the daily results in the literature. Barber et al. (2022, Section D.1) analyze the potential impact of one feature of the RH smartphone app that displays the list of top movers' stocks. More precisely, they examine the relation between RH investors' position openings for stocks belonging to the top gainers (stocks with the highest positive returns) or top losers (stocks with the lowest negative returns) list. Keeping the differences between our daily analysis empirical frameworks and theirs in mind, we now contrast our results (Fig. 2) with the comparable results reported by Barber et al. (2022) in the graph on the left in Panel B of Figure 4 in their paper.

First, both our and their analyses show that RH investors react strongly to stocks with extreme positive and negative returns (top gainers and top losers). Second, they also identify that RH investors open slightly more accounts in stocks with contemporaneous extreme positive returns than those with contemporaneous extreme negative returns. That said, their numbers are an order of magnitude larger than ours. Specifically, we find a daily change of about 30 accounts per day in response to contemporaneous extreme returns, while they find this number around 300. This difference could be attributed to the differences in empirical designs. For example, they consider 20 groups for returns, while we only consider six groups. Thus, it is not surprising that the change in the number of RH users is bigger in response to more extreme returns.

Welch (2022)'s findings suggest that RH investors react to previous day's extreme price movements and that this effect is stronger for large stock price increases than for large price decreases. Put differently, he identifies an asymmetry favoring big gainers over big losers. Conversely, Fedyk (2024) finds that RH investors invest relatively more after observing extreme negative returns than after extreme positive returns in the previous day. Our daily results align with those in Welch (2022) in that we also find that the number of RH investors holding a stock increases at a faster day on days after positive extreme returns than on days after negative extreme returns.

Overall, despite noting some differences regarding behavior #2 likely stemming from different empirical designs, our daily results and those in the literature share the same major highlights: RH investors tend to react strongly to extreme returns. This suggests that the comparisons between our own daily and high-frequency results are relevant. Collectively, our comparisons demonstrate that a higher-frequency analysis reveals nuances in RH investors' trading behavior that cannot be simply extrapolated from daily observations—depending on the frequency of evaluation, different trading patterns emerge. Specifically, the asymmetry of reaction to extreme returns may be underestimated using daily data. Furthermore, RH investors may react faster to large negative price movements than previously believed based on daily analysis.

3.3.3. Other explanations and implications

We argue that the observed patterns in RH investors' reactions to extreme price movements are related to attention-induced trading and contrarian buying behavior following extreme negative returns. There are, of course, other potential explanations for some of the patterns identified. Also, our findings might have implications for the investor trading strategies following extreme returns. In this section, we first discuss other potential explanations for our findings before turning our attention to their implications for RH investors' trading activities.

First, RH investors' inability to short-sell could explain the asymmetry in RH investors' reaction to extreme negative versus extreme positive returns (behavior #2). However, we believe this is unlikely. To see this, consider two scenarios where RH investors *can* short-sell. In the first scenario, they only short-sell stocks that experienced large positive returns. In this case, the observed asymmetry would be even more pronounced. In the second scenario, they only short-sell stocks that experienced large negative returns. In this case, the asymmetry would indeed be less pronounced. As our study, as well as those by Barber et al. (2022) and Welch (2022), suggests that RH investors tend to buy stocks that experienced large negative or positive returns, the RH investors' inability to short-sell can only explain the observed asymmetry under very specific assumptions regarding the selling demand by RH investors who own the stock and short selling demand by those who do not own the stock following extreme positive and negative returns.[15]

Second, some of the observed patterns could be due to funding liquidity constraints RH investors face when trying to buy. RH investors might be willing to buy more than they actually buy, but they cannot because they face constraints when using leverage. For example, Heimer and Simsek (2019, p.2) argue that "leverage is a major catalyst of speculative trading, because it increases the scope for extreme returns, and enables investors to take larger positions than what they can afford with their own money". They show that a leverage constraint in the retail foreign exchange market reduces trading volume by 40%. In other words, if RH investors cannot take larger positions than they can afford with their own money, their reaction will be dampened. However, we find that RH investors tend to buy following both extreme positive and negative returns. Unless this funding liquidity constraint is more stringent following extreme positive returns, we expect it to affect RH investors' buying behavior symmetrically and thus cannot account for their observed trading pattern.

Third, another potential explanation is portfolio rebalancing. Calvet et al. (2009) analyze the trading decisions of individual investors in Sweden using their annual portfolio holdings. Among other findings, they note that the absolute value of the return on a stock has a positive

[15] To see this, suppose that short selling by RH investors is allowed and their total buying and selling demands for a given stock, which is the sum of the selling demand by RH investors who own the stock and short selling demand by those who do not own the stock, are the same following extreme positive and negative returns. Considering their short-selling demand, we should not observe any asymmetry in their overall reaction to extreme negative and positive returns. In such a scenario, the observed asymmetry would result from the short-selling constraint if and only if the short-selling demand is higher than the selling demand following extreme negative returns, and the opposite holds following extreme positive news with very similar magnitudes.

effect on the probability that a household will sell it. This effect is much stronger for stocks with positive returns than those with negative returns. In other words, they find that winners are more likely to be sold than losers. If this is also the case at the daily level, then some investors will be selling the winners and thus might explain our results. However, we should note that their results are based on the annual holdings of traditional individual investors while we analyze the intraday trading behavior of different types of retail investors. For these reasons, we do not believe that the portfolio rebalancing motives of RH investors can fully explain their observed trading patterns.

Fourth, automated trading strategies might be another potential explanation. However, to our knowledge, RH did not provide an official API for automated trading during our sample period. Developers utilized unofficial methods to interact with RH's platform, including reverse-engineered APIs and third-party libraries. These tools allow programmatic access to account information, market data retrieval, and trade execution. However, users would receive warning emails from RH saying that RH cannot allow them to transact on the platform using an API. Furthermore, even if automated trading were used for trading on the RH platform, they had to be programmed to buy less (or sell more) the winners, that is, more geared towards profit taking, to explain some of the patterns observed. For these reasons, we do not believe automated trading strategies can explain our findings.

Our findings might also have implications for RH investors' trading activities following extreme returns. Meshcheryakov and Winters (2022) analyze changes in different types of intraday trading activity following intraday changes in retail investor attention, measured by the changes in hourly number of Google searches. They distinguish between three types of retail trading activity: (i) informed trading demanding liquidity, (ii) uninformed trading providing liquidity, or (iii) noise trading by uninformed traders who believe that they are informed. Their analysis first establishes that heightened Google search activity correlates with increased trading volume. They attribute this rise primarily to retail investors rather than institutional investors, based on the observation that retail traders typically place smaller orders, leading to a decline in the average order size following spikes in Google search activity. Building on these findings, they differentiate between the three types of retail trading by examining bid–ask spreads. If retail investors were truly informed after searching for a company, the bid–ask spread would be expected to widen. However, their results show no statistically significant evidence of widening spreads following surges in Google search activity. This aligns with Barber and Odean (2008), who predict that increased retail investor attention can create temporary buying pressure on a stock. Ultimately, they conclude that retail investors seem to exert buying pressure and engage in directional trading and that this is consistent with two types of trading behavior, namely informed and noise trading. In other words, they conclude that the increased retail trading activity is not due to uninformed trading providing liquidity.

Although our study differs significantly from Meshcheryakov and Winters (2022), our finding that RH investors' buying activity increases following extreme returns parallels their observation of heightened trading activity after surges in Google search volume. While conducting a similar analysis is beyond the scope of our paper, this resemblance, combined with their findings, suggests that RH investors' trading behavior after extreme returns might be largely driven by noise trading — where uninformed traders mistakenly believe they are informed — rather than by informed trading that demands liquidity or uninformed trading that provides liquidity. Additionally, the literature documenting the subsequent poor performance of RH investors' portfolios further supports this conclusion.

4. Conditional analyses of the three key behaviors

The three key behaviors outlined in the previous section are derived from examining RH investors' responses to intraday hourly and overnight price movements across a diverse range of over 2500 stocks over two years, including the initial three months of the COVID pandemic. In this section, we analyze how the reaction of RH investors to price movements varies conditional on several factors. In particular, we aim to determine if these behaviors: (i) are driven by intraday hourly or overnight movements, (ii) have changed due to the COVID pandemic, and (iii) vary with regard to firms' market capitalization.

These analyses require an adjustment of our methodological framework presented in Section 3.1. We first present this adjustment and then discuss the results of these conditional analyses.

4.1. Methodological framework

We propose a variant of regressions (4) where we allow the coefficients $\beta_g^{(L)}$ to depend on groups fulfilling certain conditions, therefore adding flexibility in exploring the behaviors conditional on the factors discussed above. Formally, we introduce a second categorical variable $I_{SGP_c}(r_{i,t_i(k-L)})$ that takes the value of one if the $r_{i,t_i(k-L)}$ observation belongs to the subgroup SGP_c, and zero otherwise. The specifications become:

$$\Delta N_{i,t_i(k-L)} = \sum_{g=1}^{6}\sum_{c=1}^{C} \beta_{g,c}^{(L)} I_{G_g}(r_{i,t_i(k-L)}) \cdot I_{SGP_c}(r_{i,t_i(k-L)}) + \mathrm{CTRL}_{i,t_i(k)}^{(L)} + \epsilon_{i,t_i(k)}^{(L)}, \tag{5}$$

for $L = 0,\ldots,5$, where the subgroup SGP contains C levels. For instance, our type-of-returns subgroup has $C = 2$ levels: overnight and intraday returns; and our size subgroup has $C = 3$ levels: small-cap, mid-cap, and large-cap.

To analyze the three behaviors conditional on these factors, we construct proxies that are linear functions of the estimates obtained in these subgroup regressions. We define each proxy as follows:

$$\begin{aligned}
&\textit{Behavior \#1:}\;\; Ext_c^{(L)} = \tfrac{1}{2}\left(\hat{\beta}^{(L)}_{<5\%,c} + \hat{\beta}^{(L)}_{\geq 95\%,c}\right) - \tfrac{1}{2}\left(\hat{\beta}^{(L)}_{[25\%,0[,c} + \hat{\beta}^{(L)}_{[0,75\%[,c}\right),\\
&\textit{Behavior \#2:}\;\; Asy_c^{(L)} = \hat{\beta}^{(L)}_{<5\%,c} - \hat{\beta}^{(L)}_{\geq 95\%,c},\\
&\textit{Behavior \#3:}\;\; SpeedExtNeg_c = \hat{\beta}^{(L=1)}_{<5\%,c} - \hat{\beta}^{(L=5)}_{<5\%,c}.
\end{aligned} \tag{6}$$

The proxy Ext quantifies the strength of the first behavior — RH investors' tendency to open more positions in stocks that exhibit extreme price movements — by evaluating the difference in the average responses to large and moderate movements. 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 toward the big losers. $SpeedExtNeg$ evaluates how fast they respond 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.

4.2. Overnight versus intraday hourly returns

We begin by distinguishing the behaviors based on the type of returns. Here, our subgroup comprises two levels ($C = 2$), distinguishing between overnight and intraday hourly return observations. We estimate the subgroup regressions accordingly and obtain 6×2 estimates for each time-lag L, allowing us to analyze the behavior of RH investors separately for each type of return.

Fig. 3 presents estimation results. The difference in magnitude in response to extreme returns is striking. For instance, the number of RH investors holding a stock increases by approximately 100 accounts per day within the opening hour after the realization of a larger negative overnight return on that stock. In contrast, the number of RH investors holding a stock increases by approximately 20 accounts per day within approximately an hour after observing a large negative intraday return. A visual examination of this figure indicates that all three behaviors are more pronounced for overnight returns. Table 5, which reports the values of our behavior proxies defined in (6), corroborates these findings.

Behavior #1. Panel A focuses on the strength of the response to extreme returns. Evaluated at one time-lag, this behavior is highly pronounced. Indeed, the value of Ext indicates that the average increase in new positions following a large overnight movement surpasses the average increase in new positions following a moderate overnight movement by 89.54 accounts per day. This is more than forty times stronger compared to the strength of this behavior with respect to extreme intraday movements (2.10 accounts per day). Through Wald tests, we find that both evaluations of our proxy are individually significantly positive, and the difference between them (87.43 accounts per day) is also significantly positive at the 1% level. Furthermore, this interpretation holds for all time-lags. Overall, these results suggest that, for the same level of extreme movements (standardized returns below -5.14 or above 5.03), RH investors open more positions when such returns occur overnight rather than intraday.

Behavior #2. Panel B contrasts the second behavior related to the asymmetric response to extreme returns. For almost all non-contemporaneous time-lags (the exception is the second lag), the differences in the evaluations of our proxy Asy are 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 to differentiate less between an upward or downward change, but when a large movement occurs overnight, they react primarily to downward moves.

Behavior #3. Panel C demonstrates that the speed of response to large negative returns is also exacerbated for overnight returns. We measure this speed at 36.85 accounts per day for overnight returns and 6.91 accounts per day for intraday hourly returns. As measured by our proxy $SpeedExtNeg$, the behaviors are individually significant, and the difference of 29.94 accounts per day is substantial and significant.[16] Therefore, RH investors tend to respond more quickly to large downward overnight price movements relative to large downward intraday price movements.

In summary, these findings underscore the significance of overnight movements. All three behaviors identified in Section 3.2 exhibit greater prominence when evaluated in relation to overnight movements. These results might also imply that some important findings reported in the existing literature based on daily data may be driven by the influence of overnight movements rather than movements occurring during regular trading hours.

Table 5
Key behaviors by type of returns – Overnight vs. Intraday hourly.

Panel A: Strength of response to extreme returns						
	Time-Lag L					
	0	1	2	3	4	5
OV	43.65***	89.54***	70.61***	60.95***	58.62***	52.27***
ID	−1.94***	2.10***	1.54***	1.27***	0.76***	0.94***
OV Minus ID	45.59***	87.43***	69.07***	59.67***	57.86***	51.33***
Panel B: Asymmetry of response to extreme returns						
	Time-Lag L					
	0	1	2	3	4	5
OV	−20.02***	13.86***	6.36*	7.76**	12.18***	10.44***
ID	−1.14*	12.48***	8.72***	5.37***	2.70***	0.73**
OV Minus ID	−18.88***	1.38	−2.36	2.39	9.48***	9.71***
Panel C: Speed of response to extreme negative returns						
OV	36.85***					
ID	6.91***					
OV Minus ID	29.94***					

Based on the $\hat{\beta}^{(L)}_{g,c}$ estimates obtained from regressions (5), this table compares the key behaviors associated to overnight (OV) versus intraday hourly (ID) return observations. In each panel, the first two rows report the value of our behavior proxy, defined in (6), specific to overnight and intraday hourly returns, respectively, and the last row takes the difference. ***, **, * indicate that the null hypothesis that the evaluated quantity equals zero is rejected at the 1%, 5%, and 10% levels.

4.3. COVID-19 pandemic

On March 11, 2020, the World Health Organization declared the outbreak of COVID-19 a global pandemic, leading to widespread lockdowns and a wave of new individuals investing in the stock market. In particular, the RH platform saw a significant influx of new users during this period.[17] 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 (Blake et al., 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. This section examines how such a shock has affected the three key RH investors' behaviors identified in the main results. We should note that we cannot answer if our findings from this analysis are a result of behavioral shifts among existing RH investors or due to a demographic transformation of RH investors amid the COVID-19 pandemic. Nonetheless, our results offer insights into the conduct of the typical RH investor in both the pre-pandemic and post-pandemic periods.

First, as illustrated in Fig. 4, our estimates show that there was a dramatic increase in the overall activity of RH users following the pandemic announcement, which is consistent with the findings of Ozik et al. (2021). In fact, the unconditional average of $\Delta N_{i,t_i(k)}$ is more than 3.5 times higher post-announcement. Moreover, all post-COVID estimates are significantly higher than their pre-COVID counterparts, indicating that RH investors have acquired more stocks in the post-COVID period.

Table 6 contrasts the three key behaviors of RH investors in the pre- and post-COVID period.

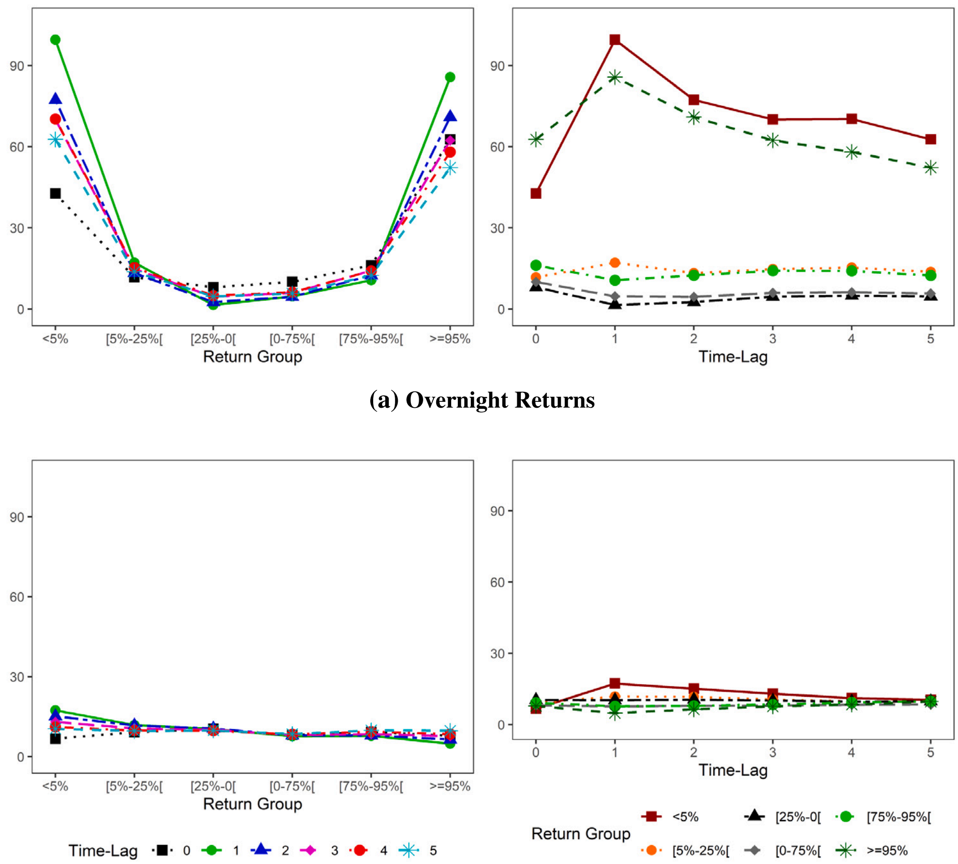
Behavior #1. RH investors' tendency to open positions in stocks that exhibit extreme returns is strong both in the pre- and post-COVID periods, as evidenced by the generally positive and significant values of Ext. However, for all time-lags, the strength of this behavior is significantly higher in the post-COVID period. For instance, before COVID, the average increase in the number of RH users holding a given stock one time-step after a realization of an extreme return is 5.84 accounts per day superior to a corresponding increase after a realization of a moderate return. After the announcement, the corresponding quantity stands at 13.29 accounts per day. The difference between the two (7.46 accounts per day) is significant at the 1% level.

Behavior #2. Our results regarding the asymmetry of response to extreme returns are more mixed. Although we do observe an asymmetry in favor of big losers both in the pre- and post-COVID periods (as almost all Asy are positive and significant), the "Pre Minus Post" differences are only statistically significant for most of the time-lags (the exception is $L = 3$) and have different signs. This suggests that the impact of the pandemic announcement on this behavior, if any, is relatively minor.

Behavior #3. The speed of response to large negative returns has increased after the pandemic announcement. When examined individually, our proxies evaluating this speed are statistically significant, indicating that both pre- and post-COVID, RH investors were particularly quick to respond to large negative returns. However, the

[16] 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 from different regressions.

[17] See, for instance, CNBC Markets, "Young investors pile into stocks, seeing 'generational-buying moment' instead of risk", May 12, 2020 or "A large chunk of the retail investing crowd started during the pandemic, Schwab survey shows", April 8, 2021.



(a) Overnight Returns

(b) Intraday Hourly Returns

Fig. 3. Key behaviors by type of returns – overnight vs. intraday hourly
This figure displays the $\hat{\beta}^{(L)}_{g,c}$ estimates obtained from regressions (5) using subgroups of either overnight or intraday hourly returns. The six regressions are estimated by pooled OLS.

difference in the $SpeedExtNeg$ proxy between the post- and pre-COVID periods (7.35 accounts per day) is statistically significant. This implies that RH investors tended to respond more rapidly to large downward price movements in the post-COVID period.

4.4. Company size

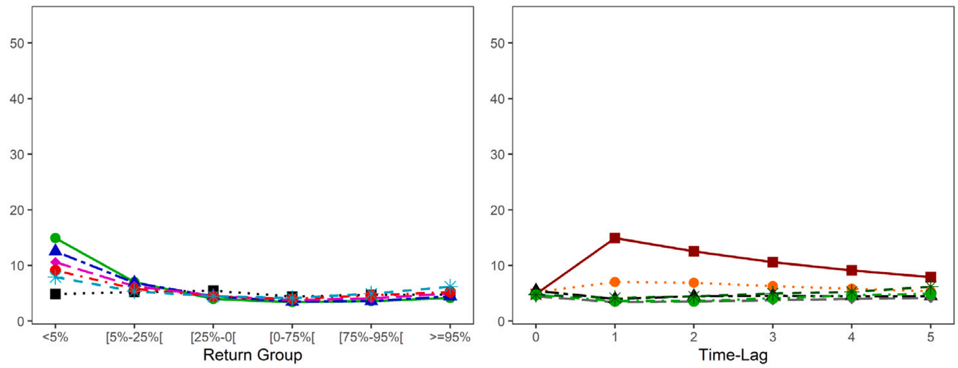
It is not clear whether retail investors prefer trading smaller- or larger-capitalization stocks. While small-cap stocks are typically less expensive, which may make them more attractive to individual investors with limited portfolio depth (*e.g.*, Chatillon et al., 2021), the increasing availability of fractional stock trading (*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 (Jirajaroenying et al., 2019; Kelley & Tetlock, 2013) and exhibit stronger herding behavior on such stocks (Hsieh et al., 2020; Venezia et al., 2011). In contrast, Welch (2022) finds that RH users' 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 (less than \$2 billion), mid-capitalization (\$2 to \$10 billion), and large-capitalization (larger than \$10 billion) — and

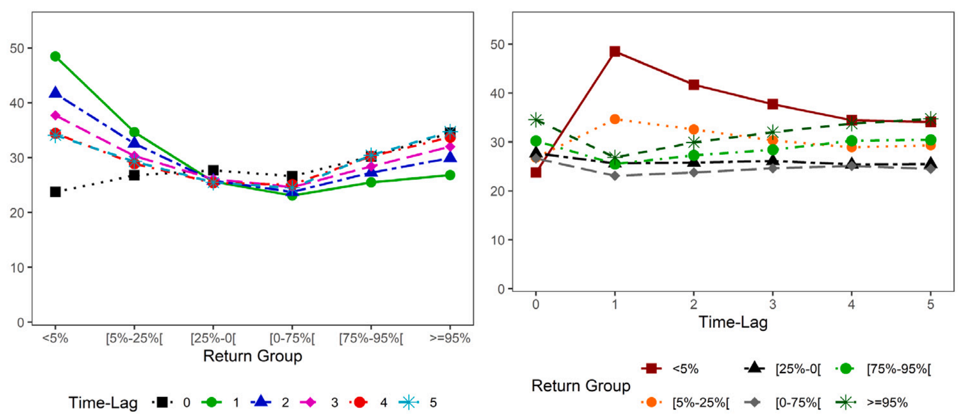
Table 6
Key behaviors pre- and post-COVID-19 pandemic announcement.

Panel A: Strength of response to extreme returns						
	Time-Lag L					
	0	1	2	3	4	5
Pre	−0.13	5.84***	4.51***	3.63***	2.96***	2.73***
Post	1.98**	13.29***	11.02***	9.50***	8.84***	9.42***
Pre Minus Post	−2.11***	−7.46***	−6.52***	−5.87***	−5.88***	−6.69***
Panel B: Asymmetry of response to extreme returns						
	Time-Lag L					
	0	1	2	3	4	5
Pre	0.10	10.79***	8.11***	5.62***	3.85***	1.72***
Post	−10.77***	21.64***	11.78***	5.70***	0.69	−0.64
Pre Minus Post	10.87***	−10.85***	−3.67**	−0.08	3.16***	2.35**
Panel C: Speed of response to extreme negative returns						
Pre	7.03***					
Post	14.38***					
Pre Minus Post	−7.35***					

Based on the $\hat{\beta}^{(L)}_{g,c}$ estimates obtained from regressions (5), this table compares the key behaviors in the periods before (Pre) and after (Post) the COVID-19 pandemic announcement. In each panel, the first two rows report the value of our behavior proxy, defined in (6), specific to the pre- and post-period, respectively, and the last row takes the difference. ***, **, * indicate that the null hypothesis that the evaluated quantity equals zero is rejected at the 1%, 5%, and 10% levels.



(a) Pre-COVID-19-Announcement Period



(b) Post-COVID-19-Announcement Period

Fig. 4. Key behaviors pre- and post-COVID-19 pandemic announcement
This figure displays the $\hat{\beta}^{(L)}_{g,c}$ estimates obtained from regressions (5) using two subgroups: the pre- and post-COVID-19 pandemic announcement periods, where the date of the announcement is March 11, 2020. The six regressions are estimated by pooled OLS.

estimate the three-level subgroup ($C = 3$) regressions accordingly.[18] Estimation results are reported in Fig. 5 and Table 7.

Behaviors #1 and #2. Panel A of Table 7 shows that, across all time-lags, the differences between large-cap and mid-cap stocks and that between small-cap and mid-cap stocks are all statistically significant, indicating that RH investors are more inclined to open positions large- and small-cap extreme movers than mid-cap extreme movers. On the other hand, the differences between large- and small-cap extreme movers are not statistically significant. In fact, Fig. 5 reveals that, for the mid- and large-cap categories, this "reaction-to-extreme" behavior is predominantly driven by extreme negative returns, with minimal evidence of a U-shape or even a smirk pattern. This finding suggests that the second behavior, which pertains to the asymmetry of RH investors' reactions to extreme returns, is notably influenced by firm size. Panel B of Table 7 corroborates this, demonstrating a monotonic increase in Asy with stock size. Taken together, these results demonstrate that, within the small-cap segments, RH investors tend to open positions on both past big losers and big gainers. Conversely, in the largest-cap segments, RH investors' inclination to buy extreme movers is significantly skewed towards the big losers.

Behavior #3. The speed at which RH investors respond by opening positions following a large negative movement is found to be highest for the large-cap category. This is evident from the differences reported in Panel C of Table 7, with (L Minus M) and (L Minus S) being both positive and statistically significant at the 1% level. Hence, RH investors take less time to open new positions after observing an extremely negative return in large-cap stocks, while comparatively more time is taken for mid-cap or small-cap stocks.

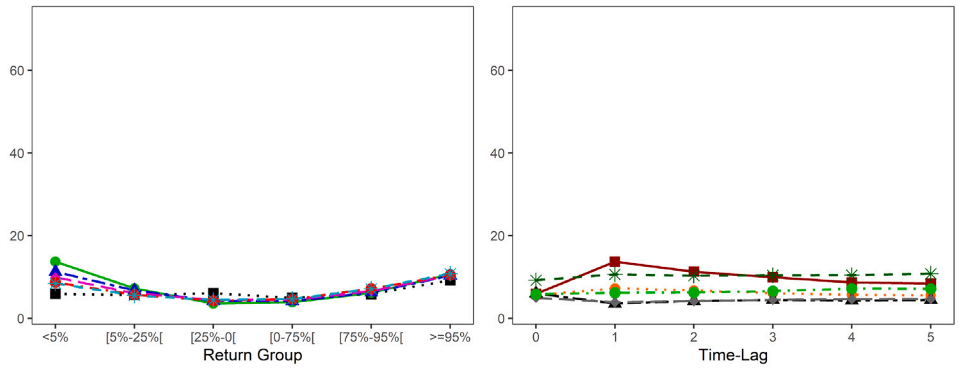
5. Robustness tests

Our results are robust across various alternative settings. In this section, we briefly present the results of different robustness tests that we deemed relevant, while more detailed information is provided in Section III of the online appendix.

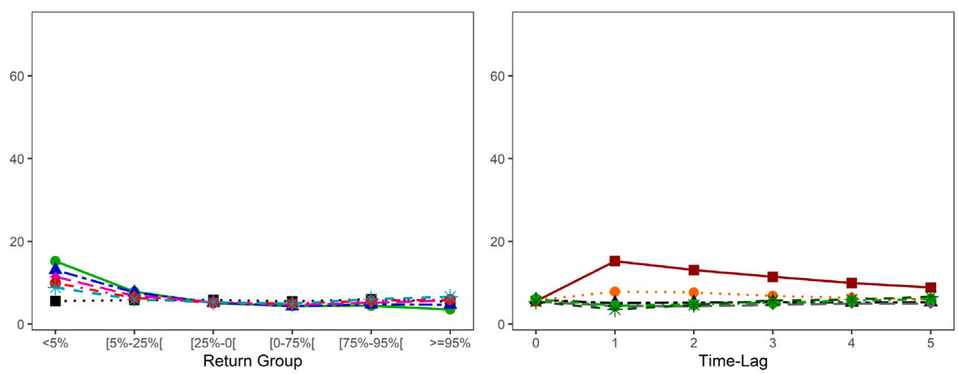
5.1. Alternative timestamps' delays regarding the original robintrack observations

As mentioned in Section 2.1, there is a delay of approximately 45 min embedded in the original timestamps of the user holding counts observations provided by Robintrack. Our main results are, therefore, based on a 45 min delay. As robustness tests, we consider alternative delays of 30 and 60 min to construct the $N_{i,t_i(k)}$ variable and re-estimated our models presented in (4). Our empirical conclusions remain quantitatively and qualitatively valid under these assumptions.

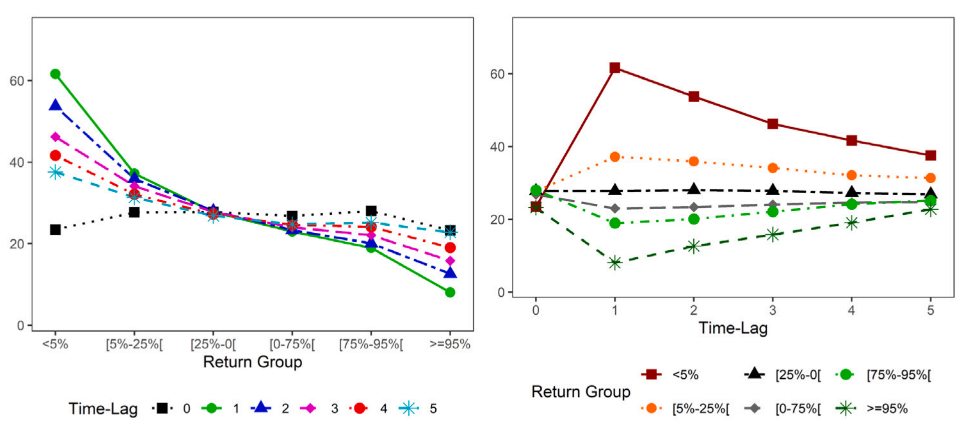
[18] We calculate market capitalization using share prices and the number of shares outstanding from CRSP. The Financial Industry Regulatory Authority (FINRA) provides size thresholds that are used to divide the universe of stocks into five categories, including micro-cap and mega-cap. In our analysis, we classify micro-cap as small-cap and mega-cap as large-cap. Due to data unavailability for eight stocks, our sample size for this analysis is slightly reduced compared to the original sample.



(a) Small-Cap Stocks



(b) Mid-Cap Stocks



(c) Large-Cap Stocks

Fig. 5. Key behaviors by company size
This figure displays the $\hat{\beta}^{(L)}_{g,c}$ estimates obtained from regressions (5) using three subgroups based on company market capitalization. The six regressions are estimated by pooled OLS.

5.2. *Fixed-effect regressions*

The three key behaviors we present in Section 3.2 are the results of our estimations of the pooled OLS models presented in (4). Our empirical conclusions remain quantitatively and qualitatively valid when we consider a model with firm and date-time fixed effects.

5.3. *Time trend: Controlling for the rise in the number of RH users*

Since the period of our study, from June 2018 to August 2020, is characterized by the increasing popularity of the RH platform among investors, there is a positive trend in the new positions opened by RH investors due to the success of RH. Therefore, the average change in the new position openings is positive and significantly different from zero. To ensure our results are not driven by this positive trend in our dependent variable, we add a trend control to our models presented in (4). We test for two cases. First, we consider a single trend (per stock) for the entire period of our sample. Second, because the increase in new accounts on the RH platform is particularly pronounced after the announcement of the global pandemic, we consider two separate trends in the pre- and post-announcement periods. Our empirical conclusions remain quantitatively and qualitatively valid under these settings.

Table 7
Key behaviors by company size.

Panel A: Strength of response to extreme returns						
	Time-Lag L					
	0	1	2	3	4	5
S	2.06***	8.44***	6.63***	5.72***	5.10***	5.06***
M	−0.17	4.67***	4.09***	3.62***	2.84***	2.62***
L	−3.95***	9.45***	7.48***	5.1***	4.43***	4.36***
M Minus S	−2.23***	−3.77***	−2.54***	−2.10***	−2.25***	−2.44***
L Minus M	−3.78***	4.78***	3.38***	1.48**	1.59**	1.74**
L Minus S	−6.01***	1.00	0.84	−0.62	−0.66	−0.69
Panel B: Asymmetry of response to extreme returns						
	Time-Lag L					
	0	1	2	3	4	5
S	−3.27***	3.06***	0.95*	−0.47	−1.76***	−2.37***
M	0.11	11.69***	8.41***	5.70***	3.99***	2.25***
L	0.23	53.54***	41.10***	30.40***	22.60***	14.77***
M Minus S	3.39***	8.63***	7.46***	6.16***	5.74***	4.62***
L Minus M	0.12	41.86***	32.69***	24.70***	18.62***	12.52***
L Minus S	3.50	50.49***	40.15***	30.87***	24.36***	17.14***
Panel C: Speed of response to extreme negative returns						
S	5.28***					
M	6.38***					
L	24.06***					
M Minus S	1.09					
L Minus M	17.68***					
L Minus S	18.77***					

Based on the $\hat{\beta}_{g,c}^{(L)}$ estimates obtained from regressions (5), this table compares the key behaviors across firm size categories (S: small, M: medium, L: large). In each panel, the first three rows report the value of our behavior proxy, defined in (6), specific to small-, mid- and large-cap stocks, respectively, and the last rows show pairwise differences. ***, **, * indicate that the null hypothesis that the evaluated quantity equals zero is rejected at the 1%, 5%, and 10% levels.

5.4. Additional controls and conditioning variables

We consider additional controls in our main models presented in (4) that might affect our results. Specifically, we add (i) the level of the VIX index, (ii) the level of the Economic Policy Uncertainty (EPU) index (Baker et al., 2016), (iii) the level of a business condition index (Aruoba et al., 2009), and (iv) an investor sentiment index (the Investor Sentiment Survey published by the American Association of Individual Investors). Re-estimating our models under this setting does not materially affect our empirical conclusions.

We also consider subsample analyses based on high/low levels (*i.e.*, above and below median levels) of these four variables. These subsample analyses yield quantitative and qualitative results similar to our main results.

5.4.1. Alternative independent variable: Returns non-standardized by volatility

One might argue that, being presumably non-sophisticated investors, RH investors do not assess extreme returns in relation to their volatility, as we defined in (3), but just look at returns alone, or returns in excess of the market. We therefore consider two alternative definitions of extreme returns, “raw returns” $R_{i,t_i(k)}$ as defined in (2), and raw returns in excess of market returns $ExRet_{i,t_i(k)} = R_{i,t_i(k)} - R^{MKT}_{t_i(k)}$. Re-estimating our models presented in (4) under this setting does not materially affect our empirical conclusions.

6. Conclusion

Robinhood investors are younger and less experienced than traditional retail investors. Their ultra-connectedness enables them to access new information more easily and quickly. Given this propensity, we argue and demonstrate that analyzing their trading behavior at the hourly intraday and overnight frequencies, rather than the daily frequency used in the existing literature, is more appropriate. Indeed, RH investors exhibit within-the-day and overnight trading behaviors that either differ from their daily behavior or cannot be identified using daily data.

We find that RH investors do not or cannot react to contemporaneous returns as the change in the number of RH investors holding a stock is not related to the stock’s contemporaneous return. On the other hand, they react significantly to lagged intraday hourly or overnight returns and exhibit three high-frequency trading behaviors: (i) the number of RH investors increases more for stocks with extreme lagged returns in the previous intraday or overnight period than for those with moderate lagged returns, potentially suggesting an attention-driven buying; (ii) this reaction to extreme lagged returns is asymmetric in the sense that the number of RH investors increases more in the period immediately following extreme negative returns compared to extreme positive returns, suggesting that their contrarian buying is stronger than their momentum buying; (iii) this asymmetry in RH investors’ reaction to extreme negative versus positive returns is much more pronounced in the immediately-following period and gradually decreases and disappears after several periods. Contrasting these high-frequency behaviors with those found in the previous literature based on daily data, we reveal that the asymmetry in RH investors’ reactions to extreme negative and positive returns is underestimated with daily data.

We also analyze these behaviors conditional on several factors, highlighting RH investors’ differential attention and behavior towards specific market segments. We find that the behaviors mentioned above are more pronounced for overnight returns than intraday returns, suggesting that RH investors pay particular attention to “pre-market” returns. This finding also points out that the daily-based results proposed by the current literature could be driven by overnight rather than intraday movements. In line with previous studies (Eaton et al., 2022), we observe a heightened general buying activity following the announcement of the COVID-19 pandemic. More precisely, in the post-COVID period, RH investors were even more inclined to buy large movers, and their speed of opening positions in response to large negative price movements accelerated. Furthermore, our results highlight that RH trading attitudes significantly vary across firm size with a more contrarian buying strategy towards larger-cap firms.

RH investors’ trading behavior has significant implications for financial markets, and existing literature has primarily analyzed these effects at lower frequencies, such as daily and monthly. To the best of our knowledge, little is known about how RH investors’ trading activity influences financial markets at the intraday level. For instance, how do the trading patterns we identify impact intraday return volatility and liquidity dynamics, and what are the implications of these effects on intraday stock prices? The answer to these and similar questions based on an intraday analysis would provide important insights into the role of intraday retail trading on financial markets. We leave these important questions for future research.

Acknowledgments

We thank the Editor (Samuel Vigne), three referees, and Yuxin Zhou for their valuable comments. We are also thankful for suggestions and comments from participants at the following conferences: SWFA 2022 in New Orleans, USA, SCSE 2022 in Montreal, Canada, EFMA 2024 in Lisbon, Portugal, AFFI 2025 in Dijon, France. We also thank https://www.cascad.tech and Christophe Pérignon for the careful validation of the reproducibility of our results. The paper won the “Cascad best reproduced paper award” at the AFFI Conference 2025. We are grateful to the Swiss National Science Foundation (grant #179281), the Natural Sciences and Engineering Research Council of Canada (grant RGPIN-2022-03767), the Group for Research in Decision Analysis (GERAD), and the Chaire Fintech AMF-Finance Montréal for their financial support.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.irfa.2025.104369.

Data availability

The authors do not have permission to share data.

References

Andersen, T. G., Bollerslev, T., & Huang, X. (2011). A reduced form framework for modeling volatility of speculative prices based on realized variation measures. *Journal of Econometrics*, *160*, 176–189.

Aruoba, S. B., Diebold, F. X., & Scotti, C. (2009). Real-time measurement of business conditions. *Journal of Business & Economic Statistics*, *27*(4), 417–427.

Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring economic policy uncertainty. *Quarterly Journal of Economics*, *131*(4), 1593–1636.

Barber, B. M., Huang, X., Odean, T., & Schwarz, C. (2022). Attention induced trading returns: Evidence from robinhood users. *Journal of Finance*, *77*, 3141–3190.

Barber, B. M., & Odean, T. (2008). All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. *Review of Financial Studies*, *21*(2), 785–818.

Barndorff-Nielsen, O. E., Hansen, P. R., Lunde, A., & Shephard, N. (2009). Realized kernels in practice: Trades and quotes. *Econometrics Journal*, *12*(3), C1–C32.

Ben-David, I., Franzoni, F., Kim, B., & Moussawi, R. (2022). Competition for attention in the ETF space. *Review of Financial Studies*, *36*, 987–1042.

Berkman, H., Koch, P. D., Tuttle, L., & Zhang, Y. J. (2012). Paying attention: Overnight returns and the hidden cost of buying at the open. *Journal of Financial and Quantitative Analysis*, *47*(4), 715–741.

Blake, M., Shah, A., & Astorino, L. (2022). *The future of capital markets: Democratization of retail investing*: *Technical Report*, World Economic Forum, Insight Report – August.

Calvet, L. E., Campbell, J. Y., & Sodini, P. (2009). Fight or flight? Portfolio rebalancing by individual investors. *Quarterly Journal of Economics*, *124*(1), 301–348.

Chatillon, E., Degryse, M., & Frenay, S. (2021). Retail investors and their activity since the COVID crisis: Younger, more numerous and attracted by new market participants. *Technical Report.*, Autorité des Marchés Financiers (AMF France).

Eaton, G. W., Green, T. C., Roseman, B., & Wu, Y. (2022). Retail trader sophistication and stock market quality: Evidence from brokerage outages. *Journal of Financial Economics*, *44*, 502–528.

Fedyk, V. (2024). *This time is different: Investing in the age of robinhood*: *Working paper*, http://dx.doi.org/10.2139/ssrn.4112307.

Fisch, J. E. (2022). GameStop and the reemergence of the retail investor. *Boston University Law Review*, *102*(6), 1799–1860.

Friedman, H. L., & Zeng, Z. (2022). *Retail investor trading and market reactions to earnings announcements*: *Working paper.*, http://dx.doi.org/10.2139/ssrn.3817979.

Gempesaw, D., Henry, J. J., & Velthuis, R. (2022). Piecing together the extent of retail fractional trading. *Global Finance Journal*, *54*, Article 100757.

Glosten, L. R., Jagannathan, R., & Runkle, D. E. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. *Journal of Finance*, *48*(5), 1779–1801.

Heimer, R., & Simsek, A. (2019). Should retail investors' leverage be limited? *Journal of Financial Economics*, *132*(3), 1–21.

Hsieh, S.-F., Chan, C.-Y., & Wang, M.-C. (2020). Retail investor attention and herding behavior. *Journal of Empirical Finance*, *59*, 109–132.

Jirajaroenying, S., Wolff, C., & Ekkayokkaya, M. (2019). *Retail investors are not noise traders*: *Working paper*, URL: https://cepr.org/voxeu/columns/retail-investors-are-not-noise-traders.

Jones, C. S., Pyun, S., & Wang, T. (2022). *Return extrapolation and Day/Night effects*: *Working paper*, http://dx.doi.org/10.2139/ssrn.4181093.

Jones, C. M., Reed, A. V., & Waller, W. (2021). *When brokerages restrict retail investors, does the game stop? Working paper*, http://dx.doi.org/10.2139/ssrn.3804446.

Kelley, E. K., & Tetlock, P. C. (2013). How wise are crowds? Insights from retail orders and stock returns. *Journal of Finance*, *68*(3), 1229–1265.

Linnainmaa, J. T. (2010). Do limit orders alter inferences about investor performance and behavior? *Journal of Finance*, *65*(4), 1473–1506.

Liu, L. Y., Patton, A. J., & Sheppard, K. (2015). Does anything beat 5-minute RV? A comparison of realized measures across multiple asset classes. *Journal of Econometrics*, *187*(1), 293–311.

Lou, D., Polk, C., & Skouras, S. (2019). A tug of war: Overnight versus intraday expected returns. *Journal of Financial Economics*, *134*(1), 192–213.

Meshcheryakov, A., & Winters, D. B. (2022). Retail investor attention and the limit order book: Intraday analysis of attention-based trading. *International Review of Financial Analysis*, *81*, Article 101627.

Moss, A., Naughton, J. P., & Wang, C. (2024). The irrelevance of environmental, social, and governance disclosure to retail investors. *Management Science*, *70*(4), 2626–2644.

Onishchenko, O., & Ülkü, N. (2022). Investor types' trading around the short-term reversal pattern. *International Journal of Finance & Economics*, *27*(2), 2627–2647.

Ozik, G., Sadka, R., & Shen, S. (2021). Flattening the illiquidity curve: Retail trading during the COVID-19 lockdown. *Journal of Financial and Quantitative Analysis*, *56*, 2356–2388.

Petersen, M. A. (2009). Estimating standard errors in finance panel data sets: Comparing approaches. *Review of Financial Studies*, *11*(1), 435–480.

Santos, D. G., Candido, O., & Tófoli, P. V. (2022). Forecasting risk measures using intraday and overnight information. *North American Journal of Economics and Finance*, *60*, Article 101669.

Seasholes, M. S., & Wu, G. (2007). Predictable behavior, profits, and attention. *Journal of Empirical Finance*, *14*, 509–610.

Ülkü, N., Ali, F., Saydumarov, S., & İkizlerli, D. (2023). COVID caused a negative bubble. Who profited? Who lost? How stock markets changed? *Pacific-Basin Finance Journal*, *79*, Article 102044.

Van der Beck, P., & Jaunin, C. (2021). *The equity market implications of the retail investment boom*: *Working paper*, http://dx.doi.org/10.2139/ssrn.3776421.

Venezia, I., Nashikkar, A., & Shapira, Z. (2011). Firm specific and macro herding by professional and amateur investors and their effects on market volatility. *Journal of Banking & Finance*, *35*(7), 1599–1609.

Welch, I. (2022). The wisdom of the Robinhood crowd. *Journal of Finance*, *77*(3), 1489–1527.

Yuan, Y. (2015). Market-wide attention, trading, and stock returns. *Journal of Financial Economics*, *116*(3), 548–564.

Zhang, L., Mykland, P. A., & t Sahalia, Y. A. (2005). A tale of two time scales: Determining integrated volatility with noisy high-frequency data. *Journal of the American Statistical Association*, *100*(472), 1394–1411.