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D. Ardia, C. Aymard, T. Cenesizoglu

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GERAD HEC Montréal
3000, chemin de la Côte-Sainte-Catherine
Montréal (Québec) Canada H3T 2A7

Tél. : 514 340-6053
Téléc. : 514 340-5665
info@gerad.ca
www.gerad.ca

Fast and furious: A high-frequency analysis of Robinhood users' trading behavior

Online Appendix

David Ardia [a]

Clément Aymard [a, b]

Tolga Cenesizoglu [b]

[a] *Department of Decision science, HEC Montréal & GERAD, Montréal, (Qc), Canada, H3T 2A7*

[b] *Department of Finance, HEC Montréal & GERAD, Montréal, (Qc), Canada, H3T 2A7*

david.ardia@hec.ca
clement.aymard@hec.ca
tolga.cenesizoglu@hec.ca

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Abstract : A growing body of recent literature analyzes the reaction of Robinhood (RH) investors to price movements at the daily frequency. As these investors tend to be more connected to the markets than traditional retail investors, we expect they react faster to new information and exhibit intraday trading behavior different from their daily trading behavior. We thus analyze RH investors' reactions to intraday hourly and overnight price movements. Differently from the previous literature, we find that RH users strongly favor big losers over big gainers. In line with our expectation, we also find that they react rapidly, typically within an hour, when acquiring stocks following extreme negative returns. Further analyses suggest greater (lower) attention to overnight (intraday) movements and exacerbated behaviors during the COVID-19 pandemic. Moreover, these trading behaviors vary significantly across firm size and industry, with a more contrarian strategy towards larger-cap firms and a heightened activity on energy and consumer discretionary stocks.

Keywords : Attention-induced trading, Robinhood, retail investors, high-frequency data, reaction speed, FinTech

This online appendix is divided into three sections. Section I describes the steps to construct our dataset. Section II presents the results at the daily level. Section III presents robustness results when using fixed-effect regressions, a detrended dependent variable, and when using 30 and 60 minutes lags.

I Dataset construction

This section details the construction and cleaning procedures employed for our two primary datasets: the Robintrack observations and the high-frequency volatility-adjusted stock returns.

I.A Robinhood observations (variables $N_{i,t_{i,k}}$ and $\Delta N_{i,t_{i,k}}$)

- Timezone. All original timestamps (UTC) are converted to New York Time (UTC-4).
- Period start. The original dataset starts on May 5, 2018 and ends on August 13, 2020. We follow Welch (2022) and remove the first month. Our sample begins on June 1, 2018.
- Timestamp's delay. The original timestamp provided by Robintrack indicates when data were retrieved from the Robinhood 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 minutes between the actual observation time and retrieval time. Therefore, to work with observation time, we subtract 45 minutes from all timestamps.[1]
- Keep only common stocks (CRSP share codes of 10 or 11).
- Dual-class securities. Up to an update fixing the issue on January 16, 2020, Robinhood's API did not differentiate between stocks with multiple classes. For example, Lennar Corporation classes A and B were both identified as LEN while they should be identified as LEN.A and LEN.B. Because of this anomaly, the number of RH users for one class is mixed with the number of RH users for the other class, leading to false results when computing the change in RH users. For another discussion of this issue, see Welch (2022). The stocks impacted by this problem were identified and removed from our sample.
- Dealing with multiple observations within or around an hour. In a few instances, Robintrack data series include more than one observation for the same stock within the same hour. These multiple observations might be duplicates (*e.g.*, 1,500 RH users hold stock i at 9.43 am, 1,500 RH users hold stock i at 9.44 am), or different (*e.g.*, 630 RH users hold stock i at 2.40 pm, 631 RH users hold stock i at 2.41 pm). We tackle the issue by retaining only one observation per hour —the last one— for each date-stock pair. In addition, if two consecutive observations for a given stock are very close to an hour sharp (*e.g.*, the closest observation to 12 pm is 11.59 am and the closest observation to 1 pm is 12.01 pm) we remove the last one.
- Keep observations within regular trading hours. Robintrack provides observations that are approximately one-hour spaced and cover the full day (*i.e.*, 24 hours). However, to be consistent with our goal to evaluate RH trading decisions in response to intraday and overnight price movements, we only focus on the changes in RH users that occur within market-opening hours (*i.e.*, hourly changes between 9.30 am and 4 pm) and overnight (*i.e.*, the change between the last observation of the day before 4 pm and the first observation of the next day after 9.30 am).
- Ensure completeness of the series at the intraday level. We retain stock-day pairs with at least six data points (combining overnight and intraday observations) available for a given day. In other words, we ensure that, for a given stock-day, there exists one intraday observation for each hour when the market is open (summing up to five or six observations), and one overnight observation. Because we retain at least six observations and keep one observation per hour, it might happen that the time length between two consecutive intraday observations deviates from

[1] Description of the problem in Barber et al. (2022): *"The Robintrack data are generally reported every hour at approximately 45 minutes after the hour. The data from Robinhood has some lag. Thus, the user count at 3:46 on Robintrack for Apple is from sometime before 3:46. Based on some analysis of open data, the likely lag is between 30 and 45 minutes."*

one hour. In the most extreme case, the series of observations could be 9.45 am, 10.45 am, 11.45 am, 1.45 pm, 2.45 pm, 3.45 pm. These cases are marginal and represent only 0.13% of the total number of observations of our final sample. In addition, this potential issue is mitigated by the fact that we scale all $\Delta N_{i,t_{i,k}}$ and $r_{i,t_{i,k}}$ to exactly one hour.

- Ensure continuity in the series at the daily level. We examine whether a given stock' series contains breaks (*i.e.*, missing days). As mentioned in Welch (2022), "*the RT script failed to run on August 9, 2018, on January 24–29, 2019 (4 days), and January 7–15, 2020 (7 days).*" This means that all stocks have a (non-fixable) break of 7 trading days. Hence, we check for stocks containing break(s) of more than seven trading days and remove them.
- Remove stocks series with no variations and treat other anomalies. We identify stocks for which $N_{i,t_{i,k}}$ is constant for the whole period and exclude them from our sample. In a few cases, the $N_{i,t_{i,k}}$ series drop abnormally to zero after a corporate event (*e.g.*, a company name change, split, etc.). We treat these cases manually by truncating the period length accordingly or excluding the stock from our sample.

I.B High-frequency returns (variables $P_{i,t_{i,k}}$, $R_{i,t_{i,k}}$, and $r_{i,t_{i,k}}$)

- Adjust prices for splits. Some securities had split(s) during our sample period. We identify such events to ensure consistency for computing returns and adjust the historical price series accordingly.
- Estimation of the daily volatility of overnight returns. We attempt to estimate a GJR-GARCH(1,1) model for each stock series using demeaned returns and normally distributed residuals. In a few cases where the algorithm could not converge, we estimate a standard GARCH(1,1) model instead. We remove the security from our sample if the algorithm does not converge. We require that the stock series contains at least 240 observations for a consistent estimation. We remove all securities that do not satisfy this condition.

I.C Filters applied to the initial dataset

Table A1 reports the number of observations and unique securities left after each filtering step, starting from the initial Robintrack dataset and ending with the final sample used in the paper.[2]

Table A1: Filters applied to the initial dataset.

Filtering Step		#Obs	#Stocks
1	Robintrack (RT) original dataset	143,337,516	8,597
2	Drop the first month (May 2018)	139,578,005	8,597
3	Apply timestamps adjustment (-45min) and keep observations within regular trading hours	38,161,939	8,597
4	Match RT tickers with TAQ and CRSP	24,475,538	8,115
5	Keep common stocks (share codes 10 or 11)	11,771,843	3,842
6	Remove dual-class stocks	11,710,325	3,830
7	Adjust for multiple observations within or around an hour	11,195,363	3,830
8	Ensure completeness of the series at the intraday level	10,871,402	3,828
9	Ensure continuity in the series at the daily level	10,659,165	3,755
10	Match RT observations with transaction prices and apply again filters 8 and 9	8,045,109	2,899
11	Compute daily realized volatility and GJR-GARCH estimators	7,801,554	2,594
12	Remove stocks with no variations in the $N_{i,t_{i,k}}$ series and treat other anomalies	7,788,538	2,583

#Obs reports the number of stock-day-time observations. #Stocks reports the number of unique securities.

[2]A discrepancy of 2,583 exists between the final number of observations reported in Table A1 and the number of observations reported in Table 1. These 2,583 entries represent missing values corresponding to the first observation of each stock series in our sample, for which $\Delta N_{i,t_{i,k}}$ cannot be computed.

II Daily frequency analysis

We define the daily-frequency variables similarly to the high-frequency variables introduced in Section 2.2. Utilizing the same panel employed for the high-frequency analyses, we isolate the last available observation before 4 pm (the "close" observation) and construct daily ("close-to-close") series of RH users' net position openings. Formally, we define:

$$\Delta N_{i,d} = \log\left(\frac{N_{i,d}}{N_{i,d-1}}\right), \tag{A.1}$$

where $N_{i,d}$ is the last observation of day d before 4.00 pm for each stock i. Similarly, we define daily volatility-adjusted returns as

$$r_{i,d} = R_{i,d}/\hat{\sigma}^{GJR}_{i,d}, \tag{A.2}$$

where $R_{i,d} = \log\left(\frac{P_{i,d}}{P_{i,d-1}}\right)$ is the series of daily ("close-to-close") log-returns of stock i and $\hat{\sigma}^{GJR}_{i,d}$ is a GJR-GARCH(1,1) daily volatility estimator computed on this series of daily returns.

The summary statistics in Table A2 highlight that the distributions of the daily measures exhibit thinner tails compared to the distributions of the high-frequency measures. For the standardized returns, this implies a greater dispersion in overnight and hourly intraday price movements, indicating the presence of price reversals within a 24-hour period. Regarding the RH user measure, it suggests that daily, the behavior of RH investors tends to be more balanced between opening new positions and liquidating existing positions in a given stock. Throughout the 24-hour period, the number of RH traders purchasing new stocks tends to be offset by the number of RH traders liquidating their positions in the same stock. However, on a higher-frequency basis—during overnight periods or one-hour periods within regular trading hours—RH investors tend to act more in concert; that is, most of them are either opening new positions or liquidating existing ones. This observation indicates the significance of RH investors' activity within the day and reinforces the importance of studying their behavior in a high-frequency setting.

Table A2: Summary statistics of main variables – Daily frequency.

	Av	Std	5th	25th	50th	75th	95th	*Nobs*	T	#
$\Delta N_{i,d}$	29.34	254.51	−232.57	−51.10	0.00	62.70	350.91	1,201,860	526	2,583
$r_{i,d}$	−0.00	1.06	−1.59	−0.52	0.00	0.54	1.52	1,201,860	526	2,583

Summary statistics as in Table 1, using daily-frequency observations.

We now turn to estimate regressions analogous to (4), where all high-frequency variables are replaced by their daily-frequency equivalent:

$$\Delta N_{i,d} = \sum_{g=1}^{6} \beta_g^{(L)} I_{\mathcal{G}_g}(r_{i,d-L}) + \mathrm{CTRL}^{(L)}_{i,d} + \epsilon^{(L)}_{i,d}. \tag{A.3}$$

Lag L now designs a "daily-lag" instead of a "time-lag." The categorical variables $I_{\mathcal{G}_g}(r_{i,d-L})$ are constructed using the same percentile ranges as for the high-frequency analysis (see Table A3). Estimation results are reported in Table A4 and Figure A1.

Table A3: Classification of standardized returns – Daily frequency.

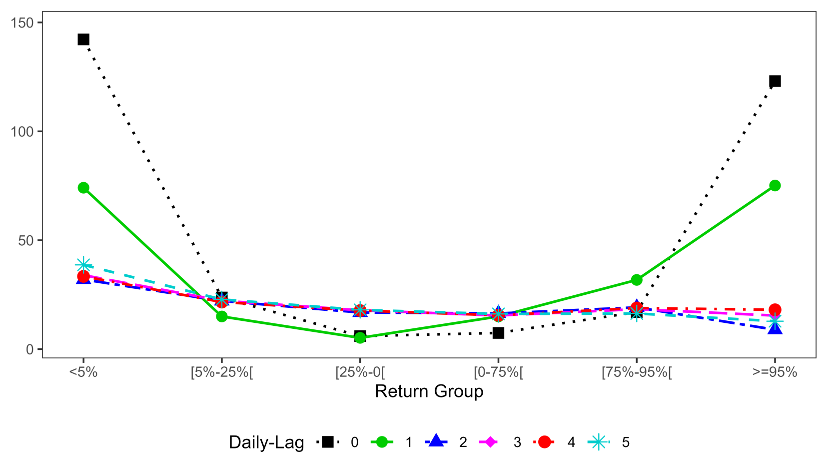
	$\mathcal{G}_1$	$\mathcal{G}_2$	$\mathcal{G}_3$	$\mathcal{G}_4$	$\mathcal{G}_5$	$\mathcal{G}_6$
PRCT	$< 5\%$	[5%-25%[	[25%-0[	[0-75%[	[75%-95%[	$\geq 95\%$
$r_{i,d}$	< -1.59	$[-1.59, -0.52[$	$[-0.52, 0.00[$	$[0.00, 0.54[$	$[0.54, 1.52[$	≥ 1.52
Nobs	60,093	240,372	286,721	3142,09	240,372	60,093

Classification of standardized returns as in Table 2, using daily-frequency observations.

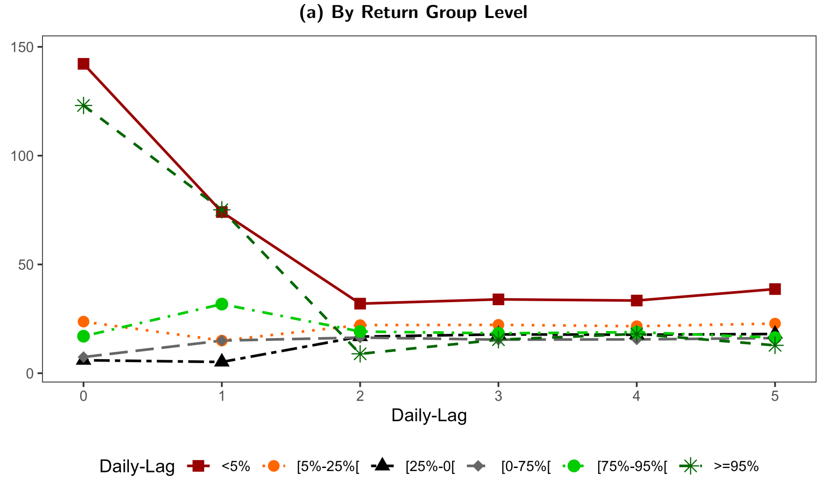
Table A4: Reaction of RH Investors to price movements – Daily frequency.

	Daily-Lag L					
	0	1	2	3	4	5
<5%	142.2	74.10	31.98	33.94	33.41	38.68
	(54.35)	(39.42)	(18.00)	(19.08)	(19.74)	(22.52)
[5%-25%[	23.71	14.99	22.12	22.24	21.62	22.81
	(28.51)	(17.73)	(19.42)	(19.90)	(19)	(19.43)
[25%-0[	5.98	5.17	16.83	17.84	17.70	18.02
	(8.94)	(6.54)	(15.62)	(16.75)	(16.57)	(17.08)
[0-75%[	7.42	14.99	16.39	15.44	15.54	16.16
	(11.25)	(18.30)	(15.00)	(14.54)	(15.15)	(15.76)
[75%-95%[	17.01	31.78	19.17	18.34	18.88	16.36
	(18.88)	(32.11)	(16.33)	(16.37)	(16.92)	(14.67)
≥95%	123.06	75.12	8.91	15.41	18.06	12.83
	(35.42)	(32.63)	(4.96)	(9.60)	(11.84)	(8.40)
$Adj.R^2$	0.026	0.025	0.022	0.022	0.023	0.022
Nobs	1,188,945	1,188,945	1,188,945	1,188,945	1,188,945	1,188,945

Estimation results of regressions (A.3), as for the high-frequency results presented in Table 3.



(a) By Return Group Level



(b) By Day-Lag

Figure A1: Reaction of RH investors to price movements – Daily frequency. Estimation results of regressions (A.3), as for the high-frequency results presented in Figure 1.

III Robustness analyses

III.A Fixed effects

In this section, we analyze the robustness of our results to the inclusion of firm and date-time fixed effects. Specifically, we estimate

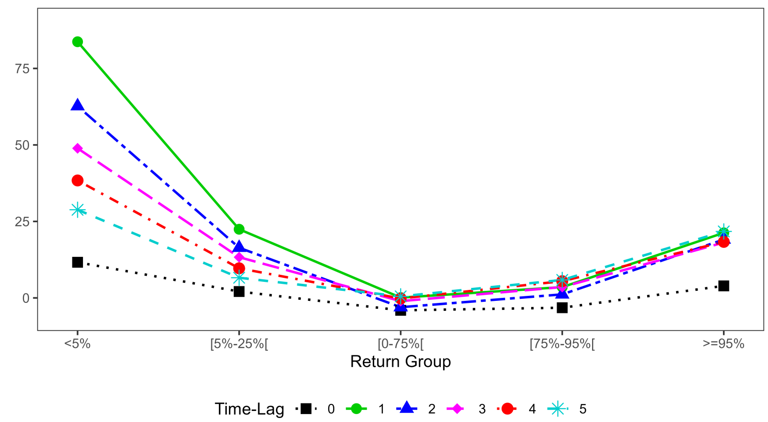
$$\Delta N_{i,t_{i,k}} = \sum_{g=1}^{5} \beta_g^{(L)} I_{\mathcal{G}_g}(r_{i,t_{i,k-L}}) + \mathrm{CTRL}_{i,t_{i,k}}^{(L)} + \lambda_i + \gamma_{t_{i,k}} + \epsilon_{i,t_{i,k}}^{(L)}, \tag{A.4}$$

where λ_i and $\gamma_{t_{i,k}}$ account for firm and date-time fixed effects, respectively. Table A5 and Figure A2 report the estimation results. Note that, to avoid collinearity issues, we use only five out of the six original return level groups. Specifically, we omit the group [25%-0[. Therefore, the results are all relative to this group. Since we are mostly interested in the reaction of RH investors to extreme returns *relative* to more moderate returns, the interpretation of our results does not change fundamentally. A simple way to interpret the coefficients would be to add the estimates of the omitted group reported in Table 3 to the estimates in Table A5. For example, the reaction of RH investors to extreme negative returns after one hour, i.e. the estimate for $L = 1$ and <5%, would be $83.72 + 24.68 = 108.40$, which is very close to the one reported in our main results (100.41). Overall, these results show that our main conclusions remain qualitatively and quantitatively unchanged.

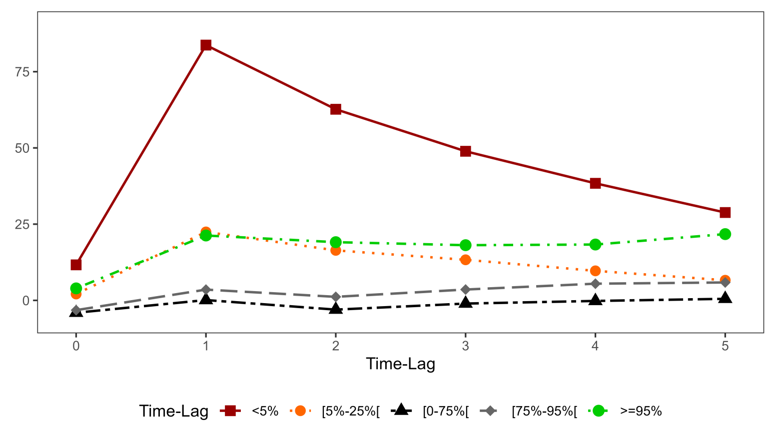
Table A5: Reaction of RH investors to price movements – With fixed effects.

	Time-Lag L					
	0	1	2	3	4	5
<5%	11.65	83.72	62.68	48.9	38.39	28.81
	(5.12)	(30.61)	(28.09)	(25.52)	(21.47)	(17.27)
[5%-25%[	2.09	22.44	16.40	13.31	9.68	6.60
	(2.59)	(23.73)	(19.51)	(16.74)	(12.99)	(8.72)
[0-75%[	-4.05	0.10	-3.03	-1.05	-0.19	0.51
	(-6.21)	(0.12)	(-4.28)	(-1.52)	(-0.29)	(0.79)
[75%-95%[	-3.20	3.53	1.16	3.55	5.47	5.87
	(-2.99)	(2.73)	(1.12)	(3.78)	(6.48)	(7.02)
≥95%	3.93	21.27	19.09	18.10	18.31	21.73
	(1.49)	(7.67)	(8.60)	(9.55)	(10.6)	(13.93)
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

Estimation results as in Table 3 with fixed effects. We removed the group [25%-0[to perform the fixed-effect estimation. Estimates are expressed in basis points. Associated t-statistics computed with robust double-clustered standard errors are shown in parenthesis.



(a) By Return Group Level



(b) By Time-Lag

Figure A2: Reaction of RH Investors to Intraday Hourly and Overnight Price Movements – With Fixed Effects. Estimation results of regressions (4) as in Figure 1 with firm and date-time fixed effects. We removed the group [25%-0[to perform the fixed-effect estimation.

III.B Detrended version of $\Delta N_{i,t_{i,k}}$

We first estimate the trend in each $\log(N_{i,t_{i,k}})$ series by OLS ($\log(N_{i,t_{i,k}}) = \alpha + \beta t_{i,k} + \epsilon_{t_{i,k}}$). Then, we construct detrended series as $N^*_{i,t_{i,k}} = \log(N_{i,t_{i,k}}) - \widehat{\log(N_{i,t_{i,k}})}$ and use this version to compute the change following our method presented in the main text:

$$\Delta N^*_{i,t_{i,k}} = \begin{cases} (N^*_{i,t_{i,k}} - N^*_{i,t_{i,k-1}}) \times SF_{INT} & \text{for an intraday change} \\ (N^*_{i,t_{i,k}} - N^*_{i,t_{i,k-1}}) \times SF_{OV} & \text{for an overnight change}\,. \end{cases} \tag{A.5}$$

Descriptive statistics are presented in Table A6. Main empirical results are reported in Table A7 and Figure A3.

Table A6: Summary statistics of net position openings – Detrended variable

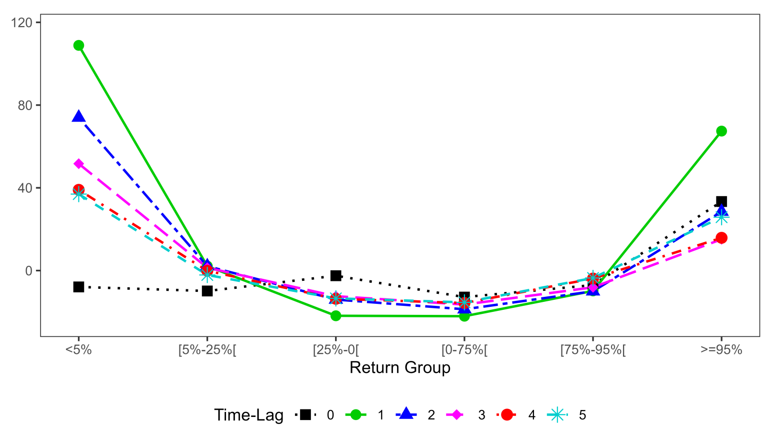
	Av	Std	5th	25th	50th	75th	95th	*Nobs*	T	#
Intraday	−14.20	1,468.37	−762.17	−139.21	−50.25	0.08	725.42	6,584,095	527	2,583
Overnight	32.21	554.46	−265.45	−48.10	−6.66	48.34	369.94	1,201,860	526	2,583
All	−7.03	1,367.85	−689.15	−122.63	−43.01	10.36	661.39	7,785,955	527	2,583

Summary statistics as in Table 1 computed on the $\Delta N^*_{i,t_{i,k}}$ series.

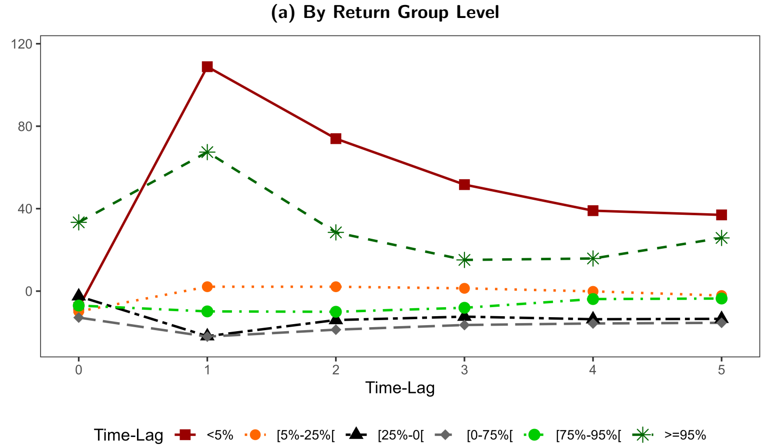
Table A7: Reaction of RH investors to intraday hourly and overnight price movements – Detrended variable

	Time-Lag L					
	0	1	2	3	4	5
<5%	−7.91	108.87	73.96	51.67	39.03	36.98
	(−2.76)	(27.71)	(23.57)	(19.77)	(17.51)	(16.33)
[5%-25%[	−9.87	2.14	2.13	1.36	-0.11	-2.13
	(−6.75)	(1.55)	(1.61)	(1.04)	(−0.09)	(−1.56)
[25%-0[	−2.50	−21.86	−14.02	−12.38	−13.64	−13.44
	(−2.08)	(−17.02)	(−10.93)	(−9.12)	(−10.49)	(−10.40)
[0-75%[	−12.82	−22.06	−18.70	−16.43	−15.70	−15.37
	(−10.11)	(−17.62)	(−14.91)	(−12.85)	(−11.85)	(−12.05)
[75%-95%[	−7.00	−9.84	−10.02	−8.08	−3.85	−3.59
	(−4.31)	(−6.41)	(−6.57)	(−5.89)	(−2.82)	(−2.64)
≥95%	33.37	67.43	28.50	15.14	15.83	25.81
	(7.44)	(13.49)	(9.04)	(5.91)	(6.35)	(10.92)
$Adj.R^2$	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

Estimation results as in Table 3 where the detrended version $\Delta N^*_{i,t_{i,k}}$ replaces $\Delta N_{i,t_{i,k}}$ as the dependent variable.



(a) By Return Group Level



(b) By Time-Lag

Figure A3: Reaction of RH Investors to Intraday Hourly and Overnight Price Movements – Detrended Variable. Estimation results of regressions (4) as in Figure 1 where the detrended version $\Delta N^*_{i,t_{i,k}}$ replaces $\Delta N_{i,t_{i,k}}$ as the dependent variable.

III.C Alternative timestamps' delays regarding the original Robintrack observations

We replicate our main results (Table 3 and Figure 1) using alternative timestamps' delays of 30 and 60 minutes, respectively.

Due to the implementation of our various data adjustment filters discussed in Section I, the samples assuming 30-min and 60-min delays differ slightly from our main sample. For instance, assuming a 30-minute delay could result in certain observations falling outside regular trading hours, such as those with an original timestamp of 4.35 pm. In rare cases, securities not included in our main sample might be present in the 30-min or 60-min samples, and vice-versa. To ensure consistency, we enforce that the 30-min and 60-min samples only include securities that are part of the main sample. The 30-min (60-min) sample contains more than 95% (98%) of the main sample securities.

Results for the 30-min delay are reported in Table A8 and Figure A4 and results for the 60-min delay are reported in Table A9 and Figure A5.

Table A8: Reaction of RH investors to intraday hourly and overnight price movements – 30-min delay.

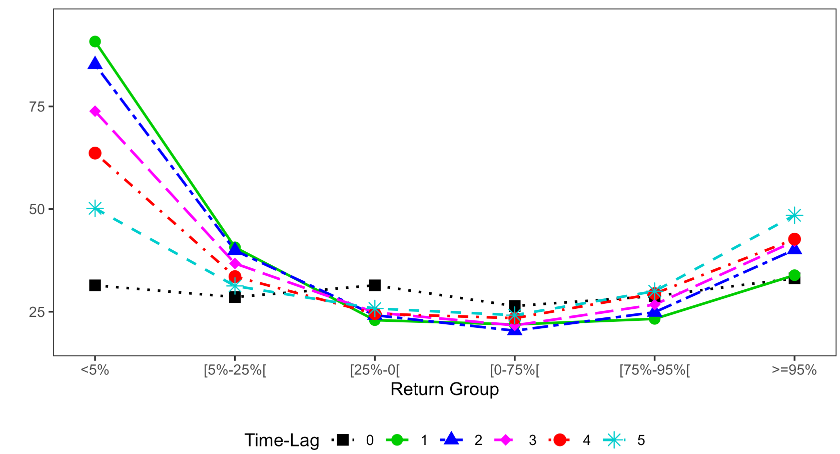
	Time-Lag L					
	0	1	2	3	4	5
<5%	31.42	90.80	85.19	73.84	63.63	50.18
	(19.47)	(50.20)	(53.42)	(51.06)	(47.07)	(38.63)
[5%-25%[	28.57	40.68	39.91	36.75	33.55	31.27
	(29.32)	(39.49)	(42.33)	(39.97)	(37.39)	(35.11)
[25%-0[	31.42	22.94	24.16	24.82	24.52	25.79
	(37.77)	(25.67)	(27.61)	(28.8)	(28.44)	(30.17)
[0-75%[	26.39	21.90	20.38	21.68	23.43	24.17
	(33.77)	(26.90)	(24.46)	(25.91)	(28.29)	(29.77)
[75%-95%[	28.80	23.26	24.88	26.74	29.40	30.00
	(31.21)	(24.28)	(27.69)	(30.66)	(33.41)	(34.29)
≥95%	33.13	33.89	40.09	42.16	42.67	48.48
	(19.32)	(17.62)	(25.05)	(29.31)	(30.79)	(36.27)
Adj.R^2	0.001	0.001	0.001	0.001	0.001	0.001
Nobs	7,010,056	7,010,056	7,010,056	7,010,056	7,010,056	7,010,056

Regression results as in Table 3, assuming 30-min timestamps' delays.

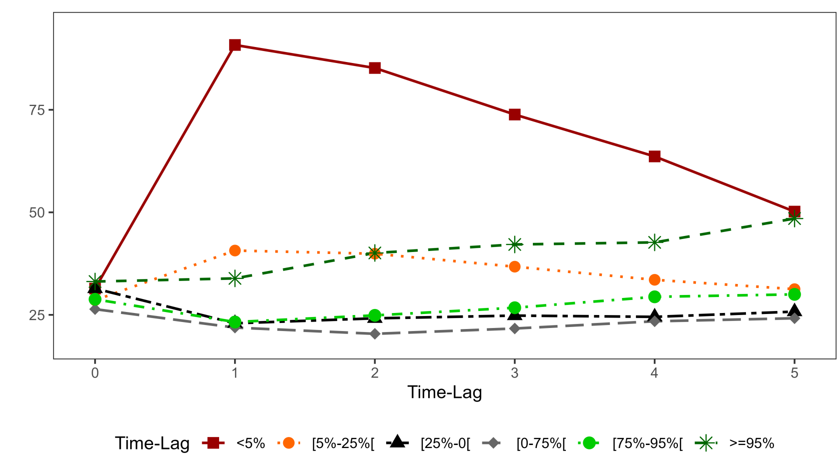
Table A9: Reaction of RH investors to intraday hourly and overnight price movements – 60-min delay.

	Time-Lag L					
	0	1	2	3	4	5
<5%	53.69	98.15	84.46	75.25	67.91	63.40
	(29.11)	(60.56)	(57.61)	(54.97)	(52.06)	(51.00)
[5%-25%[	41.30	46.18	44.63	40.59	38.93	35.90
	(40.83)	(48.76)	(50.19)	(45.77)	(45.92)	(42.92)
[25%-0[	35.53	28.24	28.95	30.13	28.96	29.69
	(44.51)	(33.27)	(34.62)	(36.59)	(35.50)	(35.81)
[0-75%[	28.31	23.21	24.08	25.54	26.63	27.70
	(37.73)	(28.44)	(29.86)	(31.55)	(32.9)	(33.90)
[75%-95%[	26.64	27.70	29.27	30.53	32.91	33.74
	(27.96)	(29.84)	(33.22)	(35.02)	(37.42)	(38.86)
≥95%	22.74	38.73	41.11	42.59	44.53	49.13
	(11.22)	(23.21)	(27.62)	(31.45)	(34.81)	(37.41)
Adj.R^2	0.001	0.002	0.002	0.002	0.002	0.002
Nobs	8,412,773	8,412,773	8,412,773	8,412,773	8,412,773	8,412,773

Regression results as in Table 3, assuming 60-min timestamps' delays.

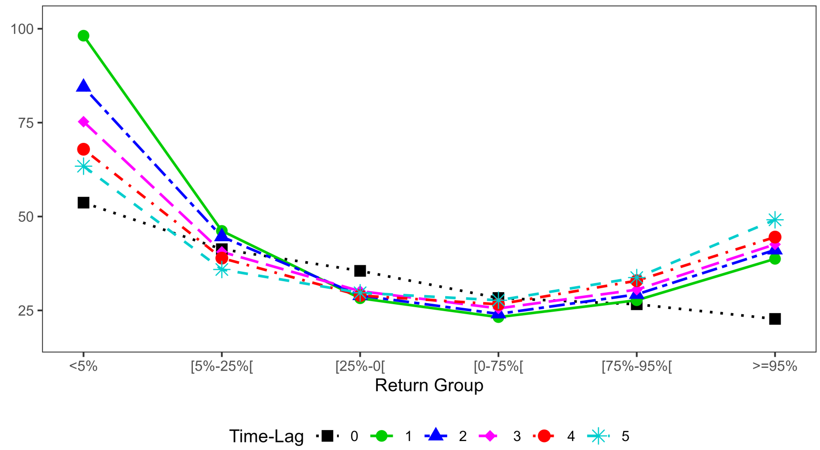


(a) By Return Group Level

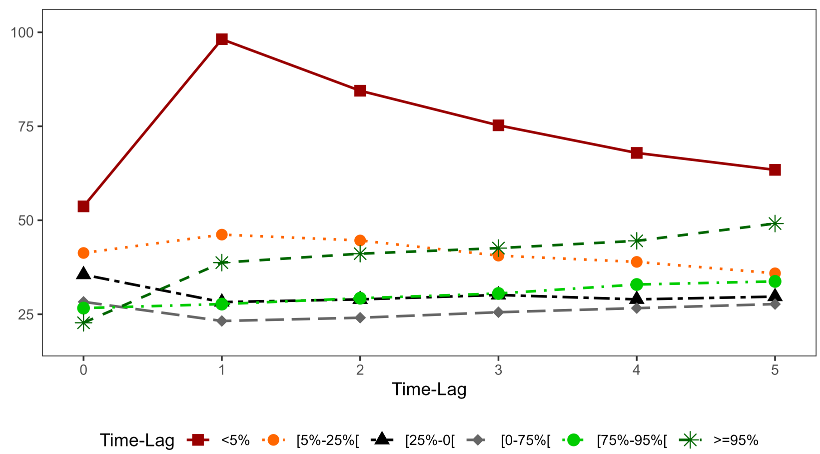


(b) By Time-Lag

Figure A4: Reaction of RH investors to intraday hourly and overnight price movements – 30-min delay. Representation of regression results as in Figure 1, assuming 30-min timestamps' delays.



(a) By Return Group Level



(b) By Time-Lag

Figure A5: Reaction of RH investors to intraday hourly and overnight price movements – 60-min delay. Representation of regression results as in Figure 1, assuming 60-min timestamps' delays.

References

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