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Retail Trading and Stock Volatility: The Case of Robinhood

By

Cooper Jones[1]

Abstract:

We examine the relation between Robinhood usership and stock market volatility. We show that daily fluctuations in Robinhood usership, which is used to proxy retail trading, significantly influence various measures of volatility. These results might suggest that Robinhood users contribute to noise trading as they are generally individuals trading on name recognition, media coverage, popularity, and familiarity of products, rather than on fundamental values. In our empirical approach, we find that the percentage increase in Robinhood usership Granger causes increases in daily stock volatility.

Keywords: Robinhood; Volatility; Retail Trading; Noise Trading

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1. Introduction

Retail trading has become more common in recent years.[2] Tools such as Robinhood allow average people to trade daily on various exchanges. All one needs is a bank account, smartphone, and a basic knowledge of how financial markets operate. Retail trading has been the cause of commotion in the media in recent weeks with coverage on Reddit's Wall Street Bets and the seemingly unpredictable price volatility of GameStop Corporation (GME). Individuals, or retail traders, do not typically trade on data, statistics, distributions, or fundamental valuations (see e.g., De Long, Shleifer, and Summers, 1989; Barber and Odean, 2008) and, thus, can contribute to the noisiness of prices in financial markets. Bloomfield, O'Hara, and Saar (2009) show that noise traders, those lacking an informational advantage, diminish the ability of market prices to incorporate new information, which is the premise of the efficient market hypothesis (Fama, 1970).

While not all retail traders use Robinhood, and not every Robinhood user is a retail trader, in this study we assume a high majority of Robinhood users are non-strategic informationally advantaged traders. Therefore, we use Robinhood as our window into retail trading and examine how it influences stock market volatility. It is important to note that volatility is often used to measure risk, meaning the more volatile a security, the riskier it is. Volatility can often dissuade traders from investing because of the risk associated with frequent and unpredictable price movements. For the risk averse traders, this could mean investing in indices or transitioning their investment portfolios into a heavier weight of bonds. For the risk takers, this means utilizing volatility for gain. Although impossible to perfectly predict, we often see traders "swinging for the fences" and betting on volatility favoring their strategy. In the recent GME debacle on institutional traders, betting that a security will fall in price only to see it rise has potentially infinite negative

[2] See the Financial Times "Rise of the retail army: the amateur traders transforming markets."

repercussions. A typical institutional trader cowers at the possibility of such great loss. It is this relationship that provides insight into the mindset of the institutional trader versus that of a retail trader. While both seek to gain from their investment, the injection of mass noise trading pollutes the forecasting performed by an institutional trader and at times limits the ability for institutional traders to see their strategy come into fruition.

The current stock trading atmosphere and continually increasing amount of volatility raises concerns on market efficiency. Among the many topics that have been debated in finance institutional traders proclaim that markets are overwhelmingly efficient - prices adjust accordingly as new information is revealed (see e.g., Malkiel and Fama, 1970; Fama; 1991). This information comes in many forms. An argument can be made that the information era which we are currently living in should theoretically increase market efficiency because information is more easily and speedily accessible today than it has been historically.

We may be experiencing a gradual shift in our markets due to the popularity of trading. A complementary shift may need to be made for institutional investors who are seeking to best predict volatility and make a gain. If the number of retail traders in the market continues to increase, professionals could start to factor in the effect on retail traders if they have not already done so. Our perception on volatile markets is also changing. A four-hundred-point drop in the DJI today is not enough of a scare to cause any worry in 2020, but the same drop ten years ago would have caused widespread panic.

Isolating Robinhood usership is key to the study because the last year has been unprecedented in many ways. We have seen the pandemic in every area of our lives, an election cycle that continues to leave half of the country in question of the integrity of our elections, trade tensions rising between the United States and China, natural disasters including drought, unmatched peacetime government spending, and many more. Reality is often outweighed by the perception of reality and is manifested in the perceived risk of an investor.

Lastly, and in the simplest of terms, volatility forecasting in practice is the ability to predict the price of a security. If in high confidence a security is forecasted to increase in price, buy in. The inverse is also true. In our study we isolate Robinhood usership and stock volatility and search for causation of Robinhood usership and stock volatility.

2. Hypothesis Development

Kyle (1985) describes noise traders as uninformed individuals who trade at random. To go further than what has been written previously, noise traders are ultimately gamblers. They are seeking heavily reported on, high priced securities that have the potential to grow by a large percentage in a short period of time. They typically trade in specific industries and look to trade on momentum caused by an apocalypse of information. Sometimes noise traders even team up and gamble in groups to increase their chances of upward volatility – as in the recent experience of the GME episode.[3]

The increase in noise trading behavior does not go without consequences and the question must be asked how Robinhood users affect widespread stock volatility. The noise-trader theory asserts that irrational investors contemporaneously respond to a noisy signal that can create systematic risk (see e.g., DeLong, Shleifer, Summers, and Waldmann, 1987; Kelly, 1997; Brown, 1999). In an experimental analysis, Bloomfield, O'Hara, and Saar (2009) show that when traders are uninformed, they hinder the ability of security prices to adjust to new information, creating greater uncertainty, and perhaps more volatility. Furthermore, the noise introduction sourced from

[3] See The Trade article "The Reddit revolt: GameStop and the impact of social media on institutional investors."

Robinhood has manifested itself in extreme examples like GameStop, Tesla, Bitcoin, and Dogecoin. We, therefore, hypothesize that an increase in Robinhood usership will increase stock price volatility.

3. Data Description

3.1. Data Sources

For our data, we obtained daily stock observations from CRSP for May 3, 2018 to December 31, 2019. Our Robinhood data comes from https://robintrack.net/ for the same period and provided the number of daily Robinhood users by stock. The website does not have more recent data, which limits our sample period.

3.2. Variable Definitions and Summary Statistics

We estimate two measures of volatility: *Rvolt* and *Gvolt*. *Rvolt* is the daily range-based volatility of Alizadeh, Brandt, and Diebold (2002), or the natural log of the high ask price minus the natural log of the low bid price. *Gvolt* is the daily volatility obtained from estimating a generalized autoregressive conditional heteroskedasticity model with one lag, which estimates autoregression and then computes autocorrelations of an error term to test for significance. To estimate retail "noise" trading, we examine both the daily number of users reported on Robinhood (*# Robinhood Users*) and the daily percentage change in the number of Robinhood users for a particular stock (*%Δ Robinhood Users*). Figure 1 illustrates the average daily Robinhood usership over our period.

[Insert Figure 1 Here]

We also include the following control variables in our empirical analysis. *Price* is the daily closing price. *MCAP* is the daily market capitalization or closing price times shares outstanding (in $billions). *% Spread* is the daily closing relative spread, or the difference between the closing ask and bid prices, scaled by the midpoint. *Illiq* is the daily Amihud (2002) illiquidity measure, or the absolute return divided by dollar volume (scaled by 106). *Turn* is the daily share turnover, or total share volume over shares outstanding.

[Insert Table 1 Here]

In Table 1, there are a few points to be made to easily digest the data. The average stock price is $39.40 for our data while our standard deviation is $86.40. This explains the vastness of our data and adds value to the breadth and depth of our dataset. We took anything and everything within our test window and these statistics show just that. Our average market cap for our data is $5.11 B with a standard deviation of $27.32 B. Again, this adds to the weight of our data. It is also of great importance to note the average number of daily Robinhood Users is 1,428 and the standard deviation is 9,840. This is a proportionally higher swing in relation to the other statistics previously mentioned. The average percentage change in Robinhood users is low, barely breaking one percent at 1.18%.

[Insert Table 2 Here]

In Table 2, our correlation matrix shows our variables and their correlations with one another. The most correlated variables are market capitalization and price, illiquidity and % spread, illiquidity and both GARCH and range-based volatility, and the two volatility measurements to each other. These findings are nothing out of the ordinary, i.e. The higher the price of a stock the larger the market capitalization, based off the simple equation market capitalization equals stock price multiplied by shares quantity. Other simple explanations exist for the other relationships, such as the proven relationship between spreads and liquidity. Money moves quicker when it has less of a price distance to travel.

Our Robinhood users have semi-strong correlation with market capitalization, which somewhat confirms our theory of the nature of Robinhood users trading large, well-known stocks. Our table also shows strong confidence in the correlation between Robinhood users and price, market capitalization, and both measures of volatility, which are both around 5%.

4. Empirical Results

In this section, we report the results from our empirical analysis. In Table 3, we observe the average stock day Robinhood usership divided into quartiles and the associated range-based and GARCH (1,1) volatility measurements for each quartile. Table 3 is a table resulting from a series of univariate tests, which focuses only on quantity. From our table we see that as the number of Robinhood users increase, both average *Rvolt* and *Gvolt* increase. Both show a statistical significance when subtracting Q1 volatility statistics to that of Q4.

A difference of 3.05% for *Rvolt* and 2.4% *Gvolt* is the difference between Q4 and Q1. These figures are huge, especially when we understand how few traders are on Robinhood compared to their great influence on prices. This aids in supporting our hypothesis that the higher the number of Robinhood traders on a single day the higher the stock volatility. On the other side of the coin, less Robinhood users could keep a stock price from reaching its forecasted potential in the mind of an institutional investor.

Our t-statistics are generous, suggesting the validity of the findings. The number of Robinhood users does appear to affect stock price volatility in the market. We find it expedient to drive home the fact that this is a measurement of stock price volatility on the average stock in the market, not just on a single stock. On a single stock that has a higher number of Robinhood users, the additional volatility could be great than or less than the average effects reported in Table 3.

[Insert Table 3 Here]

Table 4 is the results of a similar test. Where Table 3 focuses only on the quantity of Robinhood users and the effect on stock volatility, Table 4 are the statistical results of a Granger Causality in Fixed Effects Regression, which measures the movement of both range-based volatility and GARCH volatility as the percentage change in Robinhood usership moves. In Table 4, we report the results of our Granger Causality in Fixed Effects Regressions where we isolate the natural log of Robinhood users and measure both range-based volatility and GARCH volatility while fixing the other variables. This allows us to observe the change in both measures of volatility as the quantity of Robinhood users change. This test holds high reliability in our study, and we find that each additional natural log of Robinhood user adds a 23-basis point stock price range-based volatility and a 22-basis point GARCH volatility. While miniscule at a single user, we can see from our table that on days where the maximum number of users are present, volatility would be sizable for that single day. This is completely within the realm of possibilities and is a significant finding for our study.

[Insert Table 4 Here]

In Table 5 we start looking at the percentage change in Robinhood users and volatility. This is like Table 3 as we are sorting stocks into quartiles and testing how they react to certain percentage changes in Robinhood usership. Our finding here is in line with previous findings but adds a greater level of effect. We find that both types of volatility increase as a percent change in Robinhood usership increases. Basically, if more Robinhood traders are active today versus yesterday, there is more stock price volatility today than yesterday. Both test columns have statistical significance in their t-statistics, adding a great level of confidence to the study.

In each quartile of percentage change of Robinhood users, *Rvolt* and *Gvolt* changes. This has major effects on the utility of financial models in application. For example, if we were to construct a basic range-based volatility model, say in an introductory financial markets and trading university course, we might find expected volatility to live somewhere around 3% with a high degree of confidence. Take note that a simple range-based volatility model does not take into account noise and the application of our model might say that the traditional calculation of volatility could be incorrect anywhere from 2% to 4% given the percentage increase or decrease of Robinhood users compared to the day before when the *Rvolt* model was made.

[Insert Table 5 Here]

In the scope of our project, Table 6 has the most interesting finding. While the number of Robinhood users influenced stock price volatility, the percentage change in Robinhood users has a great affect. In observing Table 6, we see significantly higher statistical values for both range-based volatility and GARCH volatility measurements. This is to say that an increase in Robinhood userships from twenty-five to fifty has a greater effect on stock price volatility than increase from five hundred to five hundred and fifty. Stock prices are more volatile when there is a greater change in percentage of Robinhood users than quantity of Robinhood users.

On our assumptions about the strategy of retail traders, or rather the lack of strategy we can infer a snowball type effect on stock price volatility. If the percentage change of Robinhood users doubles day after day throughout the week and maximizes on Friday, there may be no clear way to predict volatility unless we had some way to measure in real time every single order placed on Robinhood, which we don't have. A cyclical pattern may exist where Robinhood users are creating stock price volatility, attracting more Robinhood users, increasing the percent change in Robinhood usership and then driving the stock price volatility off the charts.

This model allows for the true effects of the percentage change of Robinhood users to shine through. A mere one percent change in Robinhood users, moves stock price volatility by 184 basis points. A ten percent change in Robinhood usership, while unlikely, something like a ten percent increase in daily Robinhood usership would have huge repercussions on the volatility of markets.

[Insert Table 6 Here]

5. Concluding Remarks

In this study, we examine the relation between Robinhood usership and stock market volatility. We assume that the average trader on Robinhood is at an informational disadvantage relative to other professional traders. The noise trading theory suggests that uninformed investors may create systematic risk by coincidentally responding to the same noisy signal (see e.g., DeLong, Shleifer, Summers, and Waldmann, 1987; Kelly, 1997). In agreement with this assertion, we find that Robinhood usership has a negative impact on stock volatility both in levels and percent change tests. On high Robinhood user trade activity days, volatility increases substantially.

The number of retail traders, or even Robinhood traders is only forecasted to increase. If our findings continue in relevancy, the degree of which we observe volatility will only increase, and this is without considering further extreme examples like GameStop or other unpredictable macroeconomic factors, taxing policy, scandals, etc. In conclusion, investors' ability to accurately predict stock prices becomes more ambiguous as the popularity of retail traders, such as those on Robinhood, increases. These traders seem to be "vigilantes" that act of their own free will and continuously create noise in financial markets. There could be potential for hefty gains taking advantage of the upward volatility provided by noise traders while a clear downside exists. How long until the findings in this paper and those of a similar nature make their way into solutions for professional traders?

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Table 1. Summary Statistics

This table summarizes daily stock observations from May 3, 2018 to December 31, 2019. The following variables are first averaged by stock across the sample period. *Price* is the daily closing price. MCAP is the daily market capitalization or closing price times shares outstanding (in $billions). *% Spread* is the daily closing relative spread, or the difference between the closing ask and bid prices, scaled by the midpoint. *Illiq* is the daily Amihud (2002) illiquidity measure, or the absolute return divided by dollar volume (scaled by 10^6). *Turn* is the daily share turnover, or total share volume over shares outstanding. *Rvolt* is the daily range-based volatility, or the log of the high ask price minus the log of the low bid price. *Gvolt* is the daily GARCH(1,1) volatility. *# Robinhood Users* is the daily number of users reported on Robinhood. *%Δ Robinhood Users* is the daily percentage change in the number of Robinhood users for a particular stock.

Variable	Mean	Std. Dev.	p25	Median	p75
Price	39.4770	86.4017	10.6896	24.0778	45.1419
MCAP (in $billions)	5.1112	27.3215	0.0876	0.4133	2.0533
% Spread	0.0056	0.0114	0.0006	0.0016	0.0046
Illiq	2.9768	30.1750	0.0009	0.0068	0.0919
Turn	0.0210	0.4677	0.0035	0.0065	0.0116
Rvolt	0.0299	0.0268	0.0100	0.0224	0.0405
Gvolt	0.0241	0.0245	0.0098	0.0172	0.0309
# Robinhood Users	1,428.2900	9,840.7100	34.0811	143.4681	542.4016
%Δ Robinhood Users	0.0118	0.1770	0.0008	0.0021	0.0052

Table 2. Correlation Matrix

This table reports the Pearson correlation coefficients between the variables used in the analysis for a cross-sectional sample. We first average the sample by stock over the period May 3, 2018 and December 31, 2019. The variables have previously been defined. P-values are in brackets.

	Price	MCAP	% Spread	Illiq	Turn	Rvolt	Gvolt	# Robinhood Users	%Δ Robinhood Users
Price	1								
MCAP	0.2918	1							
	[<.0001]								
% Spread	-0.1350	-0.0851	1						
	[<.0001]	[<.0001]							
Illiq	-0.0323	-0.0183	0.4395	1					
	[0.0056]	[0.1176]	[<.0001]						
Turn	-0.0071	-0.0049	0.0133	-0.0026	1				
	[0.5418]	[0.6753]	[0.2547]	[0.8256]					
Rvolt	-0.1494	-0.0698	0.4805	0.0944	0.0851	1			
	[<.0001]	[<.0001]	[<.0001]	[<.0001]	[<.0001]				
Gvolt	-0.1321	-0.0624	0.4465	0.1061	0.1557	0.8533	1		
	[<.0001]	[<.0001]	[<.0001]	[<.0001]	[<.0001]	[<.0001]			
# Robinhood Users	0.0646	0.4276	-0.0426	-0.0136	0.0025	0.0543	0.0526	1	
	[<.0001]	[<.0001]	[0.0003]	[0.2429]	[0.8298]	[<.0001]	[<.0001]		
%Δ Robinhood Users	-0.0166	-0.0093	0.0711	0.0252	0.0115	0.1128	0.0867	-0.0042	1
	[0.1545]	[0.4250]	[<.0001]	[0.0308]	[0.325]	[<.0001]	[<.0001]	[0.7170]	

Table 3. Robinhood Users and Volatility – Univariate

This table reports the results from series of univariate tests sorting stocks into quartiles based on the average number of daily Robinhood users over the sample period. The following variables are first averaged by stock over the sample period. *# Robinhood Users* is the daily number of users reported on Robinhood. *Rvolt* is the daily range-based volatility, or the log of the high ask price minus the log of the low bid price. *Gvolt* is the daily GARCH(1,1) volatility. We test for differences in quartiles using simple student t-statistics, which we report in parentheses. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.1 levels, respectively.

	# Robinhood Users	Rvolt	Gvolt
Q1	13.47	0.0129	0.0119
Q2	77.95	0.0274	0.0211
Q3	293.14	0.0359	0.0277
Q4	5,329.23	0.0434	0.0358
Difference (Q4-Q1)	5,315.76***	0.0305***	0.0240***
t-stat	(11.90)	(38.90)	(30.32)

Table 4. Robinhood Users and Volatility – Granger Causality in Fixed Effects Regressions

This table reports the results from estimating specifications of the following fixed effects regression equation on a pooled sample of stock-day observations between May 3, 2018 and December 31, 2019:

$$Volt_{i,t}^{j} = \alpha + \beta_1 LN(\#\ Robinhood\ Users_{i,t-1}) + \beta_2 Volt_{i,t-1}^{j} + \beta_3 LN(Price_{i,t}) + \beta_4 LN(MCAP_{i,t}) + \beta_5 \%\ Spread_{i,t} + \beta_6 Illiq_{i,t} + \beta_7 Turn_{i,t} + \gamma_i + \delta_t + \varepsilon_{i,t}\ ,$$

where the dependent variable is set to one of two volatility measures: *Rvolt* or *Gvolt*. *Rvolt* is the daily range-based volatility, or the log of the high ask price minus the log of the low bid price. *Gvolt* is the daily GARCH(1,1) volatility. $LN(\#\ Robinhood\ Users_{i,t-1})$ is the independent variable of interest and equal to the natural log of the number of users on Robinhood for stock *i* on day *t*-1. *Price* is the daily closing price. *MCAP* is the daily market capitalization, or closing price times shares outstanding (in $billions). *% Spread* is the daily closing relative spread, or the difference between the closing ask and bid prices, scaled by the midpoint. *Illiq* is the daily Amihud (2002) illiquidity measure, or the absolute return divided by dollar volume (scaled by 10^6). *Turn* is the daily share turnover, or total share volume over shares outstanding. We also include by stock fixed effects, γ_i, and day fixed effects, δ_t. We report t-statistics in parentheses obtained from robust standard errors clustered at the stock level. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.1 levels, respectively.

	DV = Rvolt		DV = Gvolt	
	[1]	[2]	[3]	[4]
LN(# Robinhood Users$_{t-1}$)	0.0023***	0.0023***	0.0020***	0.0022***
	(11.66)	(12.61)	(5.97)	(5.98)
Volt$_{t-1}$	0.3239***	0.3144***	0.4549***	0.4537***
	(77.28)	(66.79)	(6.79)	(6.78)
LN(Price)		-0.0039***		0.0012*
		(-7.03)		(1.91)
LN(MCAP)		-0.0020***		-0.0020***
		(-6.70)		(-3.92)
% Spread		0.2799***		0.0202***
		(9.90)		(2.86)
Illiq		0.0000***		0.0000
		(3.77)		(0.96)
Turn		0.0008***		0.0005***
		(2.73)		(5.26)
Constant	0.0106***	0.0208***	0.0028***	-0.0032
	(9.44)	(9.07)	(3.13)	(-1.11)
Day FE	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes
R^2	0.1486	0.1639	0.2188	0.2206
N	2,567,259	2,567,259	2,566,951	2,566,951

Table 5. Percentage Change in Robinhood Users and Volatility – Univariate

This table reports the results from series of univariate tests sorting stocks into quartiles based on the average percentage change in the number of daily Robinhood users over the sample period. The following variables are first averaged by stock over the sample period. *%Δ Robinhood* Users is the daily percentage change in the number of Robinhood users for a particular stock. *Rvolt* is the daily range-based volatility, or the log of the high ask price minus the log of the low bid price. *Gvolt* is the daily GARCH(1,1) volatility. We test for differences in quartiles using simple student t-statistics, which we report in parentheses. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.1 levels, respectively.

	%Δ Robinhood Users	Rvolt	Gvolt
Q1	-0.0028	0.0230	0.0190
Q2	0.0014	0.0242	0.0187
Q3	0.0032	0.0303	0.0237
Q4	0.0456	0.0421	0.0351
Difference (Q4-Q1)	0.0484***	0.0191***	0.0161***
t-stat	(5.90)	(19.33)	(17.01)

Table 6. Percentage Change in Robinhood Users and Volatility – Fixed Effects Regressions

This table reports the results from estimating specifications of the following fixed effects regression equation on a pooled sample of stock-day observations between May 3, 2018 and December 31, 2019:

$$Volt_{i,t}^{j} = \alpha + \beta_1 \%\Delta\, Robinhood\ Users_{i,t} + \beta_2 LN(Price_{i,t}) + \beta_3 LN(MCAP_{i,t}) + \beta_4 \%\ Spread_{i,t} + \beta_5 Illiq_{i,t} + \beta_6 Turn_{i,t} + \gamma_i + \delta_t + \varepsilon_{i,t}\ ,$$

where the dependent variable is set to one of two volatility measures: *Rvolt* or *Gvolt*. *Rvolt* is the daily range-based volatility, or the log of the high ask price minus the log of the low bid price. *Gvolt* is the daily GARCH(1,1) volatility. $\%\Delta\, Robinhood\ Users$ is the independent variable of interest and equal to the percent change in the number of users on Robinhood for stock *i* between day *t* and day *t*-1. *Price* is the daily closing price. *MCAP* is the daily market capitalization or closing price times shares outstanding (in $billions). *% Spread* is the daily closing relative spread, or the difference between the closing ask and bid prices, scaled by the midpoint. *Illiq* is the daily Amihud (2002) illiquidity measure, or the absolute return divided by dollar volume (scaled by 10^6). *Turn* is the daily share turnover, or total share volume over shares outstanding. We also include by stock fixed effects, γ_i, and day fixed effects, δ_t. We report t-statistics in parentheses obtained from robust standard errors clustered at the stock level. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.1 levels, respectively.

	DV = Rvolt		DV = Gvolt	
	[1]	[2]	[3]	[4]
%Δ Robinhood Users	0.0184***	0.0182***	0.0018***	0.0016***
	(3.52)	(3.52)	(3.03)	(2.87)
$Volt_{t-1}$	0.3229***	0.3130***	0.4567***	0.4557***
	(71.73)	(63.48)	(6.82)	(6.81)
LN(Price)		-0.0055***		-0.0001
		(-9.93)		(-0.11)
LN(MCAP)		-0.0011***		-0.0013***
		(-3.75)		(-2.92)
% Spread		0.2744***		0.0152**
		(9.71)		(2.11)
Illiq		0.0000***		0.0000
		(3.79)		(0.95)
Turn		0.0007**		0.0005***
		(2.48)		(5.24)
Constant	0.0214***	0.0369***	0.0122***	0.0116***
	(44.97)	(19.54)	(8.18)	(4.92)
Day FE	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes
R^2	0.1617	0.1767	0.2181	0.2197
N	2,567,259	2,567,259	2,566,951	2,566,951

Figure 1. Average Robinhood Users

This figure plots stock-day average Robinhood usership from May 3, 2018 to December 31, 2019.