THE EFFECTS OF BOTS ON MARKET REACTIONS TO EARNINGS NEWS

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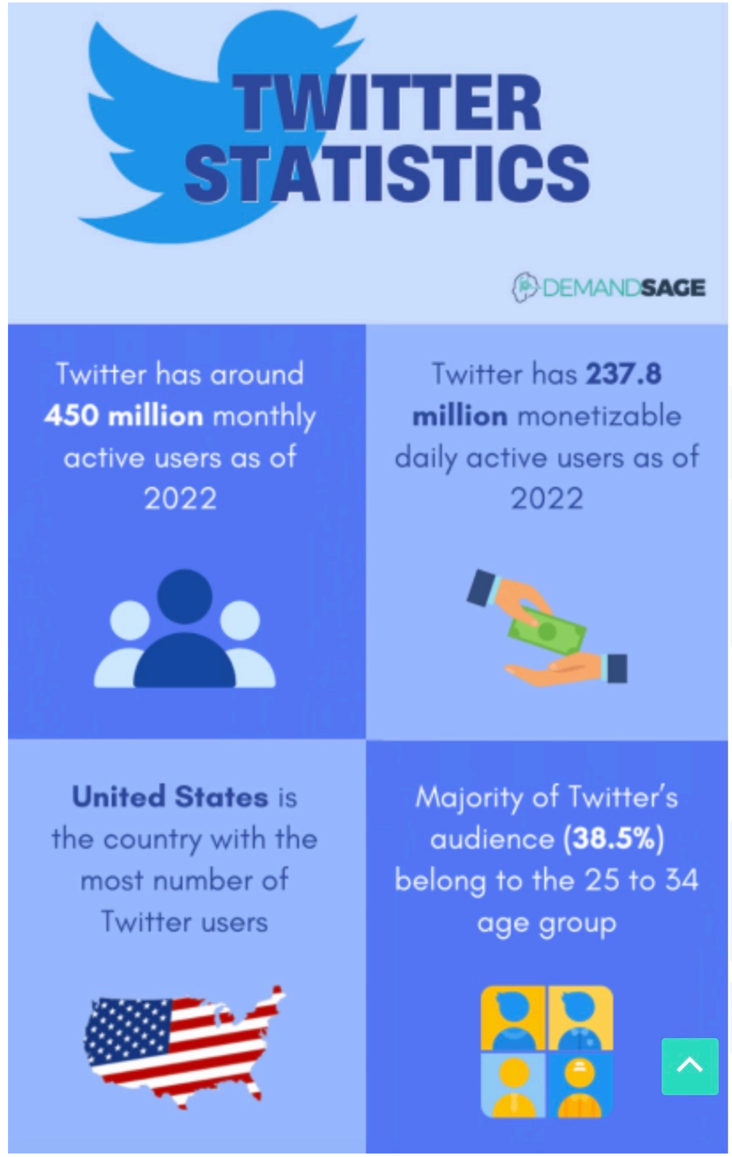
- Name
- Frequency of posts
- Number of likes and retweets
- Quality of text
- Context

- Bot's apparent purpose is to maniuver – whether to drive traffic to a blogger, to gain followers for a Twitter user, or to sell a product, service, or idea (Ferrara et al. 2016)

Category	*Sample Tweets*	*Tweet URL*
Non-Bot Tweets	Hasbro feels Toys 'R' Us woes in first quarter of 2018 #Hasbro $HAS #ToysRUs https://t.co/Ww2ccNJTdM	https://twitter.com/KnowhereNews/status/988497717788790790
	Nobody remembers. They will when prices will fall. One needs to hedge for Risk. Maybe $BCC this time? https://t.co/ALLeFmpYUC	https://twitter.com/jatin1845/status/926479354393010176
Bot Tweets	This guys making AI-based platform for analyzing indicators and generating Vigorous signals! Must have! ➡️ https://t.me/symetraplatform $MED $CLOAK $ACE ⭕ 1299637249	https://twitter.com/Heather16026903/status/1053687317792219136
	👇👇 Check Signals History 👇👇 ✅ Astonishing Prediction of Signals, All Targets Achieved Chek here ➡️ https://t.me/symetraplatform $QTUM $FUN ⭕ 1137942887	https://twitter.com/Robert15239437/status/1048782522065342464

Why Twitter?


TWITTER STATISTICS
DEMANDSAGE
Twitter has around **450 million** monthly active users as of 2022
Twitter has **237.8 million** monetizable daily active users as of 2022
United States is the country with the most number of Twitter users
Majority of Twitter's audience **(38.5%)** belong to the 25 to 34 age group

Why Twitter?

Bots comprises between 9% and 15% of active Twitter accounts (Varol et al. 2017)

Motivation of the study

- Twitter influences capital market (Bartov et al. 2018, Blankespoor et al. 2014, Lee et al.2015) .
- Not solely the domain of humans (Tardelli et al. 2020).
- Fan et al. (Fan et al. 2020) found evidence of market reactions to spikes in bot tweeting activity in discussions mentioning company Twitter accounts.
- Bot tweets have been found to is to enhance political polarization (Gorodnichenko et al. 2021)

Hypothesis Development

Building on findings showing the **polarizing effects of bots** on political markets (Gorodnichenko et al. 2021), we posit **bots increase price sensitivity to earnings information by focusing investor attention** (Lerman 2020, Nekrasov et al. 2021) on unexpected news, thereby pushing the stock price responses in the direction of the information.

Research Method

~12 million Cashtag Tweets
for S&P 1500 stocks in 2018

Felicia Davis @Felicia51342059 · 1m
$TSLA "Top analyst price target for next week --->🚀

discord.com
Discord - A New Way to Chat with Friends & Com...
Discord is the easiest way to communicate over voice, video, and text. Chat, hang out, and stay ...

MStang @StockJock22 · 39s
$AAPL will use chips built in Arizona factory

CNBC @CNBC · 8m
Official
Tim Cook says Apple will use chips built in the U.S. at Arizona factory cnb.cx/3h5iosV

News Squawker @NewsSquawker · 5m
$META finishes down 6.79% to $114.12

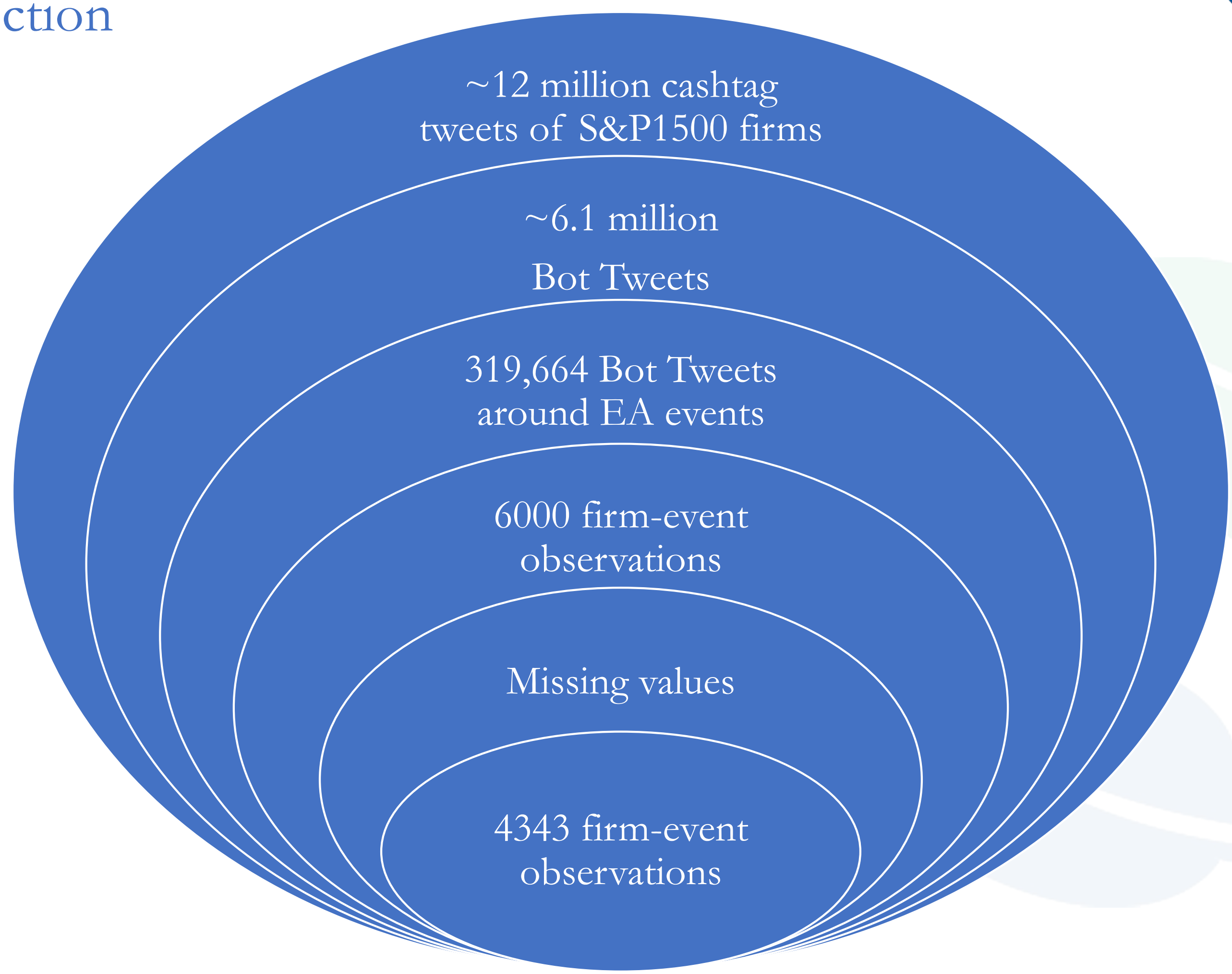
We Are Shib @weareshib · 3m
JUST IN: Tim Cook says Apple $AAPL device chips production will be moved to United States.

- We then used Python code to run all users through the Botometer (Davis et al. 2016) application programming interface (API).

- The Botometer machine learning algorithm uses over 1,000 pieces of information from each user's tweets and Twitter profile to assign a classifier score from 0 to 1, with higher scores indicating a greater likelihood the user is a bot.

- We considered accounts to be "bots" that had used a Botometer classification score threshold of 0.875 or higher

Sample Selection



Model Estimation

$$CAR_{it} = \beta_0 + \beta_1 GoodNews_{it} + \beta_2 BadNews_{it} + \beta_3 \boxed{Bot\ Activity_{it}} + \beta_4 GoodNews \times Bot\ Activity_{it} \quad (1)$$

$$+ \beta_5 BadNews \times Bot\ Activity_{it} + \sum Controls$$

$$\text{Bot Activity} = \text{Avg. daily number of bot tweets}_{[t0,\, t+1]} \;/\; \text{Avg. daily \# bot tweets}_{[t-2,t-30]}$$

For each of the firms' quarterly earnings announcement events in 2018, we measure *Bot Activity* as the number of tweets in the two-day event period (t_0, t_{+1}) divided by the number of tweets in the 30-day period (t_{-30}, t_{-2}) before the earnings announcement:

CAR

In line with previous literature (Curtis et al. 2016), we examine the market effect with a measure of cumulative abnormal returns (CAR) calculated over the t through t+1 window around each quarterly earnings announcement event.

Good News, Bad News

Difference between actual earnings and mean analyst expectation.

- Good News is coded as 1 if the earnings surprise is positive;
- Bad News, is coded as 1 if the earnings surprise is negative; and
- No News is coded as 1 if the earnings surprise is neutral.

(Mian and Sankaraguruswamy. 2012)

FINDINGS

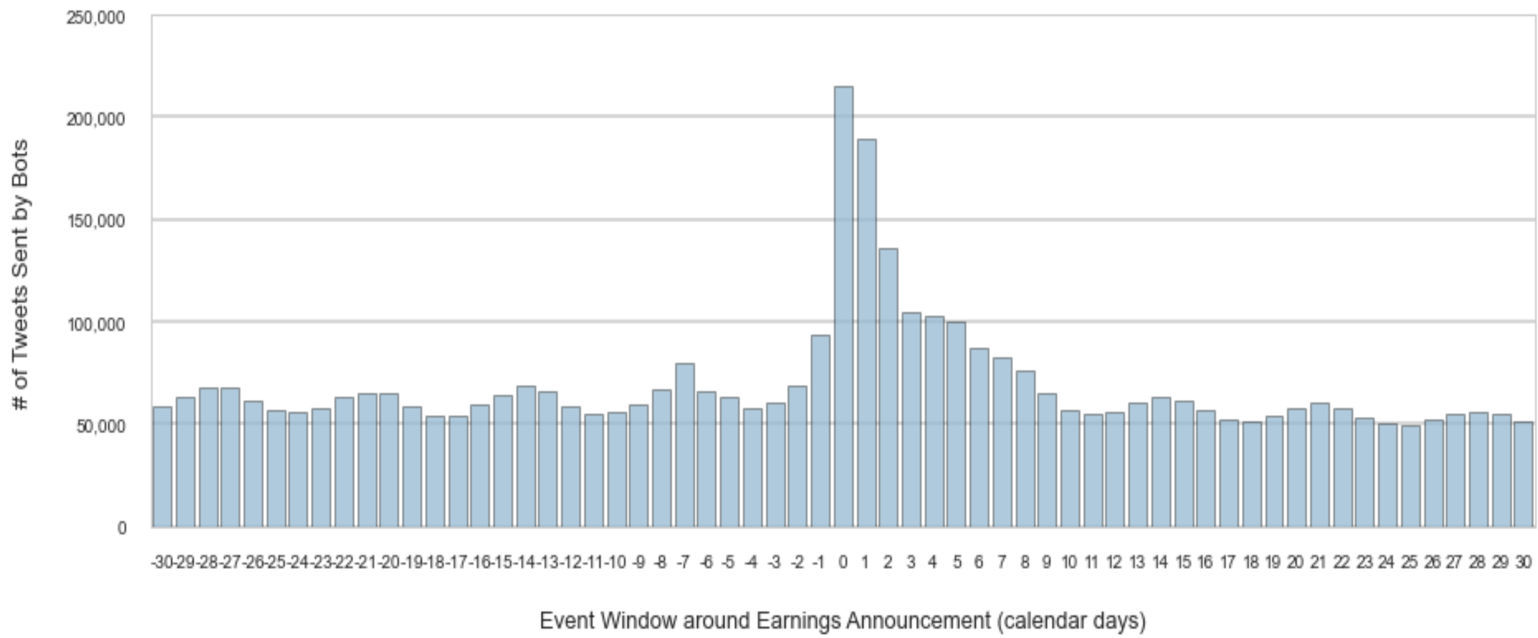


FIGURE 1. Daily Number of Tweets Sent by Bots Around Earnings Announcement Event Windows

Note: Figure presents aggregate data for 5,811 S&P 1,500 earnings announcement events (t_0) in 2018

Regression results

TABLE 4. Bot Activity and Market Reaction to Earnings News

	$CAR_{[0, +1]}$ (1)
Good News	-0.01 (0.01)
Bad News	-0.001 (0.01)
Bot Activity	-0.003 (0.002)
Good News × Bot Activity	0.01^{**} (0.002)
Bad News × Bot Activity	-0.006^{*} (0.002)
Analyst Coverage	-0.0003 (0.0002)
News Coverage	0.0001^{+} (0.0001)
Size	-0.002^{*} (0.001)
Book-to-Market	0.004 (0.003)
# of Common Shareholders	0.0002 (0.0006)
Institutional Ownership	-0.002 (0.008)
Industry Fixed Effects	YES
constant	0.02 (0.02)
Observations	4,343
Adjusted R^2	0.115

Table presents results from regression of equation (1), where the dependent variable $CAR_{[0,+1]}$ is the cumulative abnormal return around the firm's earnings announcement date, and *Bot Activity* is abnormal bot tweets. Control variables are as defined in Appendix A. Standard errors are shown in parentheses.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Investor Attention

TABLE 5. Bot Activity and Market Reaction to Earnings News by Bot Retweet Quartiles

	$CAR_{[0, +1]}$			
	Sub-Sample Based on # of Retweets of Bot Messages			
	Q1	Q2	Q3	Q4
	(1)	(2)	(3)	(4)
Good News	-0.004	0.02	-0.02	-0.02
	(0.02)	(0.03)	(0.02)	(0.03)
Bad News	-0.01	0.03	0.02	0.0009
	(0.02)	(0.03)	(0.02)	(0.03)
Bot Activity	-0.0006	0.005	-0.003	-0.005
	(0.004)	(0.006)	(0.004)	(0.005)
Good News×Bot Activity	0.005	0.002	0.01**	0.01**
	(0.004)	(0.006)	(0.004)	(0.005)
Bad News×Bot Activity	-0.006	-0.01*	-0.01*	-0.004
	(0.005)	(0.007)	(0.005)	(0.005)
Analyst Coverage	-0.0002	0.0005	0.0004	-0.0002
	(0.0005)	(0.0006)	(0.0005)	(0.0004)
News Coverage	0.0003	-0.0002	-0.0002	0.0002
	(0.002)	(0.001)	(0.0006)	(0.00010)
Size	0.0003	-0.004	-0.003	-0.004+
	(0.002)	(0.003)	(0.003)	(0.002)
Book-to-Market	0.007	0.004	-0.003	0.010
	(0.007)	(0.006)	(0.005)	(0.007)
# of Common Shareholders	-0.0006	0.002+	-0.0010	0.0009
	(0.0010)	(0.001)	(0.001)	(0.001)
Institutional Ownership	-0.003	0.003	0.01	-0.04*
	(0.01)	(0.02)	(0.02)	(0.02)
Industry Fixed Effects	Yes	Yes	Yes	Yes
Constant	0.01	0.004	-0.009	0.06+
	(0.03)	(0.04)	(0.03)	(0.04)
Observations	1,394	781	996	1,172
Adjusted R^2	0.099	0.083	0.177	0.112

Table presents results from regressions of equation (1) for four subsamples based on quartiles (Q1 through Q4 above) of the number of event-period retweets of bot messages, where the dependent variable $CAR_{[0,+1]}$ is the cumulative abnormal return around the firm's earnings announcement date, *Bot Activity* is abnormal bot tweets, and controls are as defined in Appendix A. Standard errors in parentheses. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Investor Distraction

TABLE 6. Bot Activity and Market Reaction to Earnings News with Overlapping Earnings Announcements

	$CAR_{[0, +1]}$ (1)
Good News	-0.01
	(0.01)
Bad News	0.03^{+}
	(0.02)
Bot Activity	-0.002
	(0.003)
Overlapping Earnings Announcements	0.0002
	(0.0003)
Bot Activity×Overlapping Earnings Announcements	-0.00003
	(0.00006)
Good News×Bot Activity	0.01**
	(0.003)
Good News×Overlapping Earnings Announcements	-0.00008
	(0.0003)
Good News×Bot Activity×Overlapping Earnings Announcements	0.00002
	(0.00007)
Bad News×Bot Activity	-0.01**
	(0.003)
Bad News×Overlapping Earnings Announcements	-0.0008**
	(0.0003)
Bad News×Bot Activity×Overlapping Earnings Announcements	0.0002**
	(0.00007)
Analyst Coverage	-0.0003
	(0.0002)
News Coverage	0.0001^{+}
	(0.00008)
Size	-0.003*
	(0.001)
Book-to-Market	0.005
	(0.003)
# of Common Shareholders	0.0003
	(0.0006)
Institutional Ownership	-0.0004
	(0.008)
Industry Fixed Effects	Yes
Constant	0.01
	(0.02)
Observations	4,326
Adjusted R^2	0.118

Table presents results from regressions of a version of equation (1) that adds terms interacting our coefficients of interest with a measure, *Overlapping Earnings Announcements*, of the number of other firms with the same earning announcement date. The dependent variable is the cumulative abnormal return around the firm's earnings announcement date, *Bot Activity* is abnormal bot tweets, and controls are as defined in Appendix A. Standard errors in parentheses. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Reversal

TABLE 7: Bot Activity and Reversal of Market Reaction to Earnings News

	$CAR_{[0, +2]}$ (1)	$CAR_{[+2, +20]}$ (2)	$CAR_{[+21, +40]}$ (3)	$CAR_{[+41, +60]}$ (4)
Good News	-0.02 (0.01)	-0.02^{+} (0.01)	-0.02^{+} (0.01)	-0.02 (0.01)
Bad News	-0.004 (0.01)	-0.02^{+} (0.01)	-0.02^{+} (0.01)	0.002 (0.01)
Bot Activity	-0.003 (0.002)	-0.002 (0.002)	-0.002 (0.002)	-0.003 (0.003)
Good News×Bot Activity	0.01** (0.002)	0.002 (0.002)	0.002 (0.002)	0.004 (0.003)
Bad News×Bot Activity	-0.005* (0.002)	0.004^{+} (0.002)	0.004^{+} (0.002)	0.002 (0.003)
Analyst Coverage	-0.0004 (0.0002)	0.0002 (0.0002)	0.0002 (0.0002)	-0.00005 (0.0003)
News Coverage	0.0001 (0.00008)	-0.0001^{+} (0.00008)	-0.0001^{+} (0.00008)	0.00001 (0.00009)
Size	-0.002^{+} (0.001)	-0.001 (0.001)	-0.001 (0.001)	0.002 (0.001)
Book-to-Market	0.003 (0.003)	-0.001 (0.003)	-0.001 (0.003)	-0.003 (0.004)
# of Common Shareholders	0.0005 (0.0006)	-0.00007 (0.0006)	-0.00007 (0.0006)	-0.001 (0.0007)
Institutional Ownership	-0.003 (.0009)	-0.007 (0.008)	-0.007 (0.008)	0.00006 (0.01)
Industry Fixed Effects	Yes	Yes	Yes	Yes
Constant	0.02 (0.02)	0.05** (0.02)	0.05** (0.02)	-0.01 (0.02)
Observations	4,342	4,342	4,342	4,322
Adjusted R^2	0.102	0.011	0.011	0.005

This table reports results of estimating regressions of equation (1), where the dependent variable *CAR* is the cumulative abnormal return over four different windows (as noted in headings for Models 1 – 4 above) around the firm's earnings announcement date, *Bot Activity* is abnormal bot tweets, and controls are as defined in Appendix A. Standard errors in parentheses.

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Robustness

1. Alternative Botometer score, including a more liberal threshold of 0.60 and more conservative thresholds of 0.95 and 0.99.

2. Alternative measure of bot activity that captures the number of unique actors (Abnormal Bot Users) sending cashtag tweets during each event window period.

3. Alternative versions of Good News and Bad News

4. 3-day event window for CAR[-1,+1], market-adjusted CAR in place of the market model.

5. Winsorized all continuous control variables, used the log value of the Bot Activity bot variable, included month fixed effects, and omitted the Institutional Ownership variable

Discussion

- Our findings corroborate our core hypothesis: in the presence of good earnings news, more extensive bot activity is associated with increased abnormal returns, while the opposite occurs with bad earnings news.

- Our additional analyses suggest this effect is stronger the more bot tweets are shared by other Twitter users and that bots are distorting market behavior during "high-distraction" days.

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Thank you