Online Appendix: Executive Tweets

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Executive Tweets

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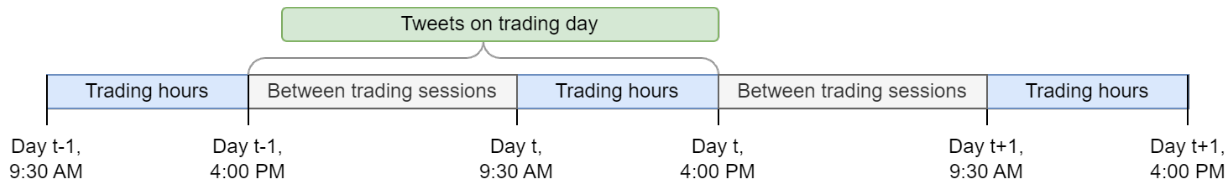
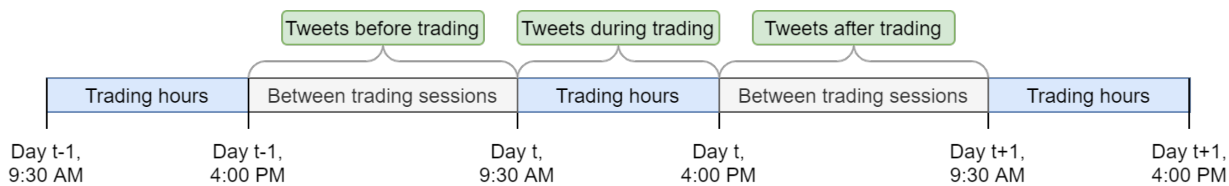
Online Appendix OA1: Timeline Illustrating Tweet Windows

Panel A: Day-level analysis window



Panel B: Intraday analysis windows



Note: Panel A shows the timing of the daily window used for analyzing tweets. The daily window starts at the end of the day *t* - 1 trading session and ends at the end of trading on day *t*. Panel B shows the three windows of tweets examined in intraday analyses: *before trading*, *during trading*, and *after trading*. *Before trading* occurs between the end of the day *t - 1* trading session and the start of trading on day *t*. *During trading* occurs during the trading session hours (9:30 AM to 4:00 PM) on day *t*. *After trading* occurs between the end of the day *t* trading session and the start of trading on day *t + 1*—this window is the same as *before trading* for day *t + 1*.

Online Appendix OA2. Twitter-LDA Model Description and Examples

We identify executive accounts using Twitter's search function, Google search, and LinkedIn profiles. We verify that each account belongs to the correct executive by examining the user description and tweet content. For instance, we compare the executives' current position (indicated on Execucomp or LinkedIn) to the information on the Twitter profile to ensure a correct match. For one account we identified, the executive deleted the account before we collected their tweets; we dropped this executive from our sample.

The Twitter-LDA model used in this paper follows the approach of Crowley et al. (2024). The model identifies 60 topics throughout a large set of tweets. The model then constructs a set of weighted dictionaries, with one dictionary representing each topic, allowing us to classify tweets into individual topics. We present three example executive tweets for each of the main topic categories we identify. We denote the presence of an image with the tag "[image]."

Financial tweets

1. "Continuing to execute in both our product & SG&A cost reduction initiatives will provide consistent EPS leverage #MDTEarnings"
2. "With ample credit, great products & strong Toyota & Honda inventory' we raised our '12 sales forecast to mid 14 million vehicles"
3. "1/ FY2015 was a transformational year. Positive operating income for the first time in 9 years! [image]"

Non-financial business tweets

1. "Arriving in Atlanta. A day meeting with customers is better than any day in the office. But I do love all the folks back in Hartford too :o)"
2. "Great time chatting with our Customer Platform team. Keep up the great work!! #LifeAtRedHat [image]"
3. "Giving keynote tomorrow at #inside3Dprinting Talking about the good, bad of #3Dprinting and the future of software"

Other tweets

1. "This won't play well in the home office, but the Flyers are making an amazing comeback against the Bruins. Series now tied 3-3. Go Philly!"
2. "Another great day of spring skiing in the Alps [image]"
3. "Hail #uncool Mother Nature showing her fury [image]"

Table OA2.1 presents the words with the highest weighting from each topic group. To provide more insight into the non-financial business topics, we present the top words based on four sub-categorizations:

marketing, support, conference, and other business. We also present the top ten words and top five bigrams tweeted by executives in each category.

Table OA2.1: Twitter-LDA top words, and bigrams

Categorization	Top 10 words	10 most frequent words used by executives	5 most frequent bigrams used by executives
Financial (1)	market, growth, markets, trading, earnings, global, report, quarter, results, energy	market, growth, results, earnings, quarter, economic, markets, year, rate, revenue	earnings call, economic growth, revenue growth, market cap, q2 earnings
Non-Financial Business (42)			
Marketing (24)	pass, free, enjoy, shipping, heres, life, love, time, #apple, shop	time, today, day, love, great, make, people, year, business, free	great time, good luck, social media, stay tuned, free stuff
Support (5)	dm, store, customer, team, flight, send, number, hear, feedback, claim	team, customer, network, service, story, great, care, share, store, change	customer service, customer experience, customer care, leadership team, team members
Conference (5)	booth, join, today, #iot, learn, great, live, week, register, stop	week, join, video, tomorrow, launch, industry, technology, today, things, supporting	youtube video, great video, breast cancer, tech industry, fireside chat
Other Business (8)	#jobs, dm, email, #job, hear, send, contact, hiring, working, details	email, customers, work, proud, support, working, world, years, future, ceo	great job, health care, years ago, pls email, hard work
Other (17)	stay, travelers, dont, rating, order, joe, tweet, collection, enjoy, book	great, good, happy, amazing, ceo, congrats, watch, day, email, love	happy birthday, woo hoo, pls email, contact blogs, great day

Note: The first column presents the name of the category or subcategory following Crowley et al. (2024), and the number in parentheses shows how many of the 60 topics found by Twitter-LDA are included in that category or subcategory. For the non-financial business category, we provide details broken out into four distinct subcategories: marketing, support, conference, and other business. The second column presents the top ten words based on the weights reported by LDA. The third and fourth columns present information on the ten most frequent words and five most frequent bigrams used by executives. For these columns, we remove all stop words using the SMART stop word list (as in Lewis et al. 2004), proper nouns, URLs, punctuation, and Twitter-specific grammar such as “RT” (which marks a message as retweeting or quoting text).

Online Appendix OA3. Twitter-LDA Validation

To validate the Twitter-LDA algorithm (Zhao et al. 2011) that we implement for determining tweets' content, we randomly select 500 executive tweets from each category: financial, non-financial business, and other. For each category we read the 500 tweets and manually classify them based on the textual content of each tweet. In Table OA3.1, we present the results of this validation as a confusion matrix, along with sensitivity (ratio of true positives to true positives plus false negatives) and specificity (ratio of true negatives to true negatives plus false positives).

We find that our financial tweet classification has the highest sensitivity of any class, indicating a low prevalence of Type II error for this classification. This is particularly important for our study, as it indicates there is a low probability that a tweet not classified as financial is financial in nature. Furthermore, our financial tweet measure likewise has high specificity at 83.5%, indicating a low prevalence of Type I error for this classification. Based on this validation, it appears that the financial tweets classification performs well and picks up almost all the financial discussion across our tweets. As financial tweets are the primary classification we examine, this validation supports the use of Twitter-LDA for our use-case.

For non-financial business and other tweets, we continue to find strong specificity and consequently low levels of Type I error; however, we do find lower sensitivity for these two classifications.

Table OA3.1: Twitter-LDA validation

	Twitter-LDA classification		
Manual classification	**Financial**	**Non-financial business**	**Other**
Financial	**60.8%**	1.2%	1.0%
	304	6	5
Non-financial business	26.2%	**70.2%**	34.0%
	131	**351**	170
Other	13.0%	28.6%	**65.0%**
	65	143	**325**
Sensitivity	96.5%	53.8%	61.0%
Specificity	83.5%	82.4%	81.9%

Online Appendix OA4. USE Method

Universal Sentence Encoder (USE) is an algorithm developed by Cer et al. (2018) for generating embeddings of sentences. An embedding is a vector that can represent a meaning within an abstract high-dimensional vector space. Other examples of embeddings include word embedding algorithms like word2vec (Mikolov et al. 2013) and GloVe (Pennington et al. 2014), which are used in the accounting literature in Brown et al. (2020). While a word embedding algorithm maps words to their meanings, a sentence embedding algorithm like USE takes this a step further, mapping whole sentences to the meaning of the sentences themselves. In the case of USE, this can be accomplished in two different ways: using a Deep Averaging Network (DAN) or a transformer architecture. For our implementation, we leverage the pre-trained transformer model provided on TensorFlow Hub.[1]

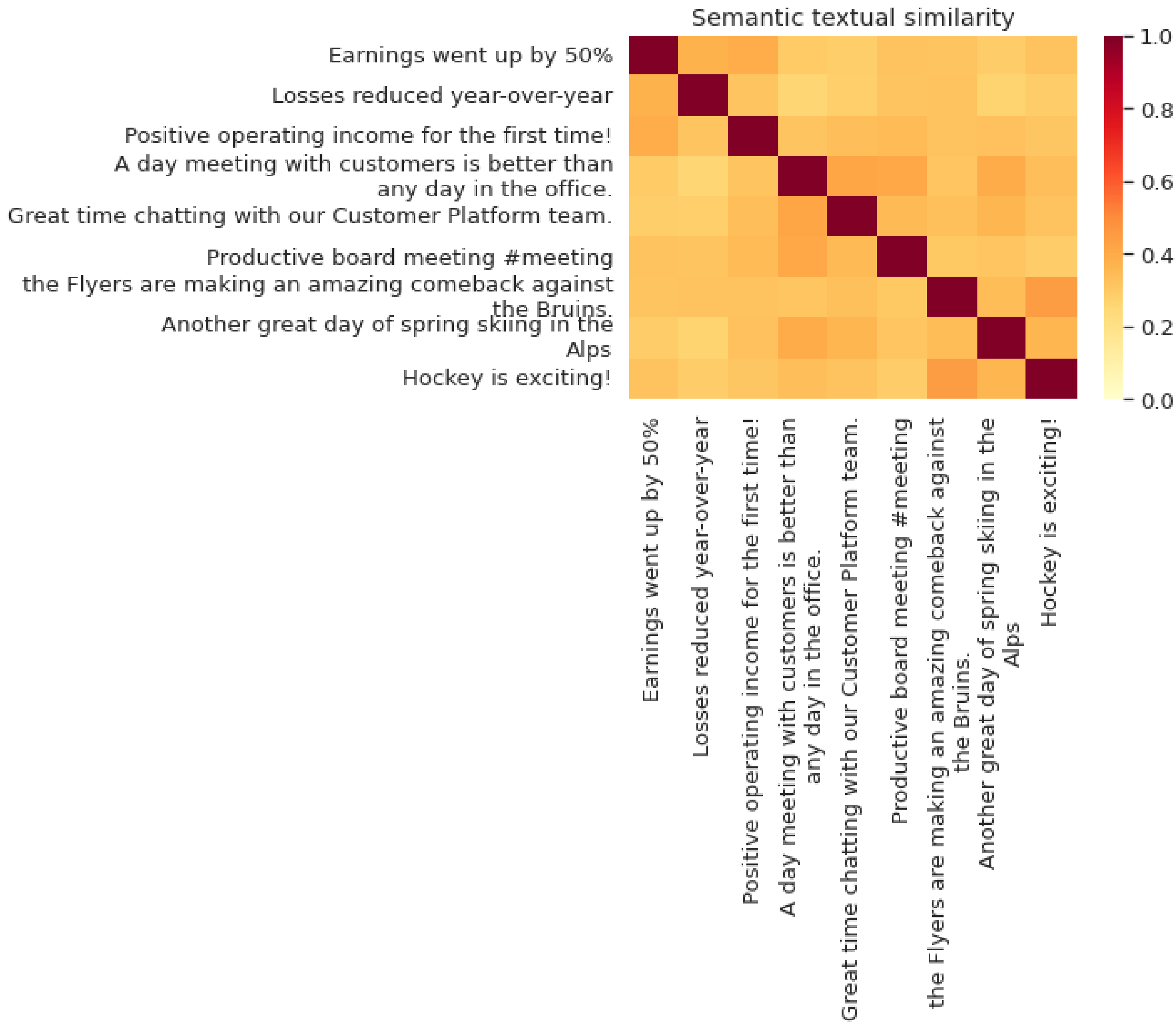
The USE methodology converts each tweet in our data into 512-dimensional unit vectors that map into a 512-dimensional vector space. Within this space, the closer two vectors are, the more similar the meaning of the two tweets that the vectors represent. To calculate the distance between vectors, our primary measure uses Euclidean (L2) distance, as this is the default distance metric used by the USE model in TensorFlow. For robustness we also calculate Manhattan (L1) distance. To convert to similarity scores, we normalize the distances such that the theoretical maximum distance becomes one. For L2 distance, we normalize by dividing by two, as the farthest distance under an L2 norm for any two n-dimensional unit vectors is two. For L1 distance in robustness checks, we normalize by dividing by $32\sqrt{2}$, as the maximum L1 distance between n-dimensional unit vectors can be calculated as $2\sqrt{n}$. Then, we subtract the normalized distance from 1 to convert to similarity.

In Figure OA4.1 below, we present an example illustrating output for a set of Twitter-like example text. The first three examples mimic financial tweets, the second three examples mimic non-financial business tweets, and the final three tweets mimic other tweets. Visually, there is clustering in the 3x3 set of cells in the upper left; this indicates that USE is picking up the similarity of these tweets as they are all

[1] The Transformer based pre-trained USE algorithm is available at: https://tfhub.dev/google/universal-sentence-encoder-large/5.

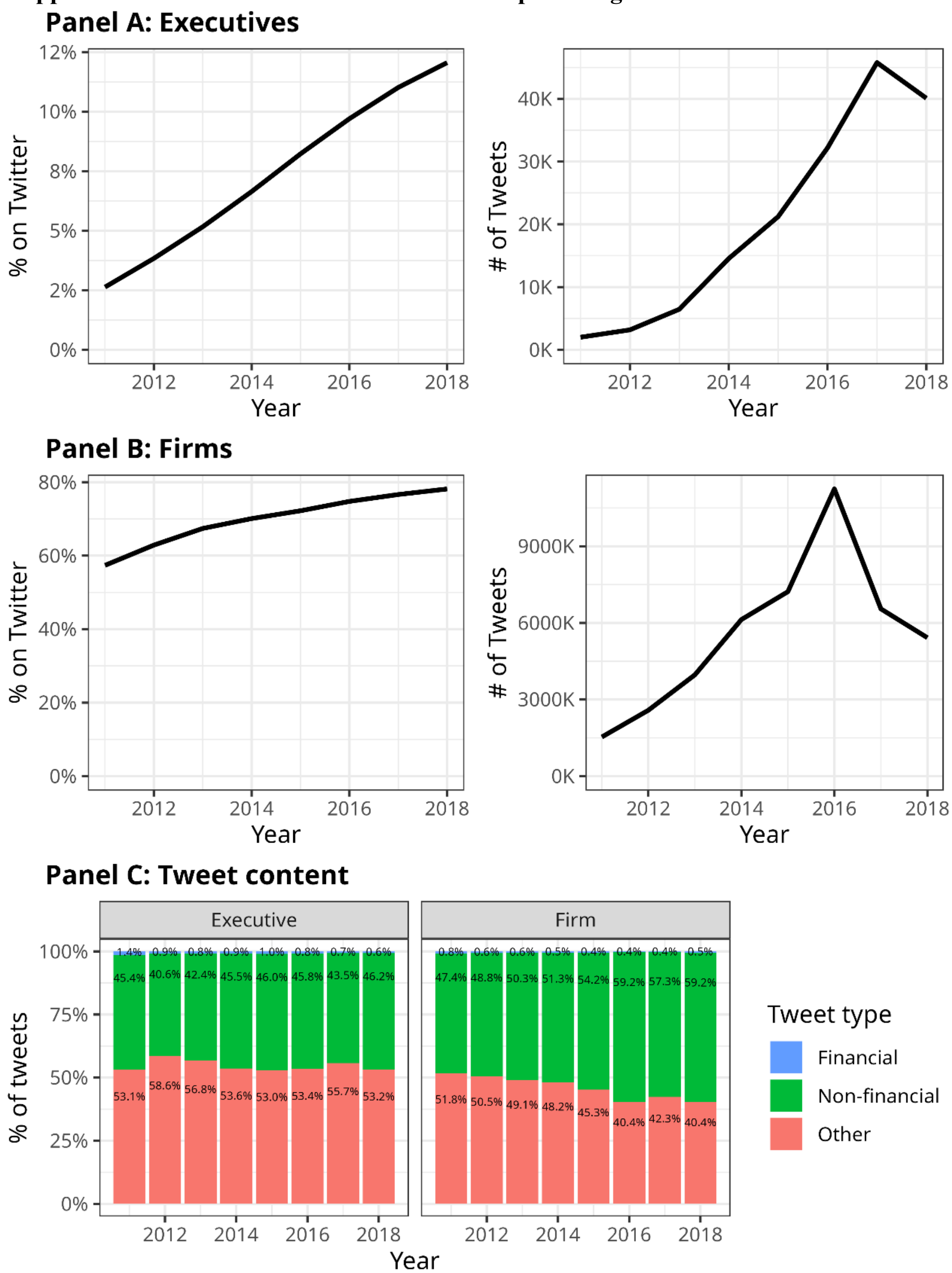
financially related. There is likewise a visual clustering in the middle 3x3 set of cells, indicating similarity within the non-financial business tweets. Lastly, two of the three other tweets show a higher degree of similarity, with one tweet explicitly talking about a hockey game and another discussing the sport more generally. Throughout all these examples, it is instructive to note that the different text snippets have very few shared words. For instance, the financial tweets use different words to indicate their financial context: earnings, losses, and operating income. In the case of the hockey example, one message contains “Flyers” and “Bruins” (team names), while the other uses the word “hockey.” This kind of matching with USE is possible because it is not sensitive to word choice. In comparison, a measure like cosine similarity applied to word counts would assign very low similarity scores to both the discussed examples, because the word choices do not overlap.

Figure OA4.1: Example Twitter-like text similarities:

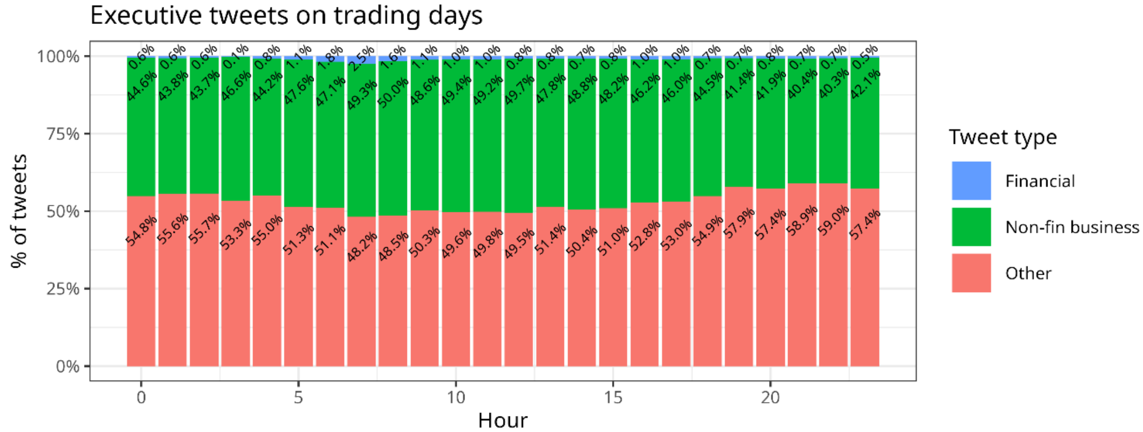


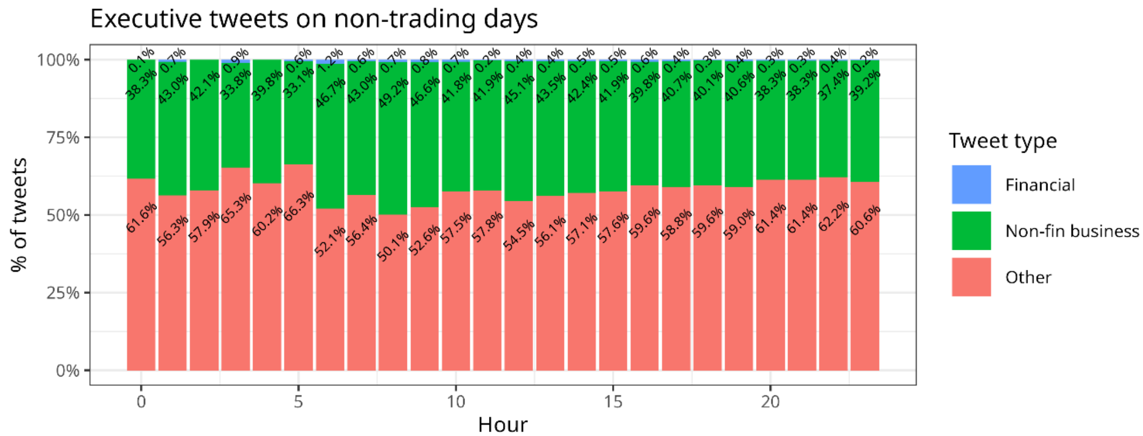
Note: This figure shows some Twitter-like text (a mix of tweets, shortened tweets, and contrived text for illustrative purposes. The first (second, third) three messages represent *financial* (*non-financial business*, *other*) content. For *financial*, note how the algorithm can pick up the similarity between "earnings," "losses" in the context of year-over-year financials, and "operating income." For *non-financial business*, it links the two tweets (first and third) about meetings as more closely related, and it picks up that the first two are related through their focus on customers. Lastly, for *other* note how for the first and third messages, it can tell that both are about hockey. The first message only mentions two team names (Flyers, Bruins) as hints that the message is hockey-related, yet it strongly matches this message with the more generic hockey-related third message.

Online Appendix 5: Executive and Firm Tweet Descriptives Figures

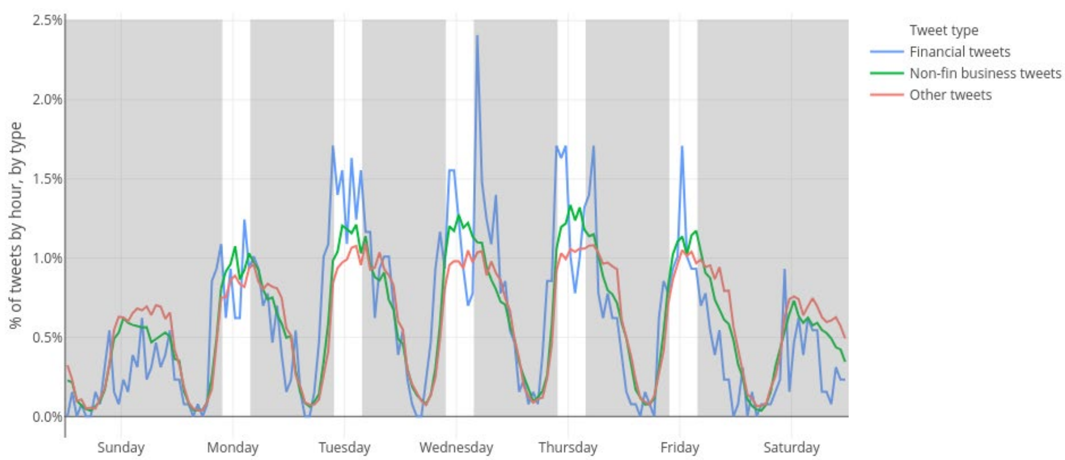


Panel D: Intraday posting time of executive tweets





Panel E: Distribution of executive tweets by hour of the week



Note: Panel A (B) presents the percentage of executives (firms) and the number of tweets by executives (firms) on Twitter by year. Panel C shows the average percentage of tweets categorized as *financial*, *non-financial business*, and *other* on Twitter by year from 2011 through 2018, split by firm and executive. Panel D shows the average percentage of tweets categorized as *financial*, *non-financial business*, and *other* on Twitter by hour, separately presenting this for trading days and non-trading days. Panel E shows the distribution of each tweet type throughout an average week, normalizing within each type of tweet. All panels are based on the full sample of executives and firms on Twitter.

Online Appendix OA6. Determinants of Executives Joining Twitter

Determinants model methodology

We use a quarterly sample at the executive-fiscal quarter level, containing 109,347 observations. We use the following logistic model to examine the determinants of executives joining Twitter:

$$Joined\ Twitter, Executive_{t,e} = \alpha + \beta_{\{1\text{-}4\}} Executive\ characteristics_{t,e} + \beta_5 Post\ SEC_t + \beta_{\{6\text{-}10\}} Financial\ controls_{t,f} + \beta_{\{11\text{-}15\}} Twitter\ controls_{t,f} + FE(Industry, Year) + \varepsilon_{t,f,e}. \quad \text{(OA1)}$$

Joined Twitter is our event of interest, and it is zero until an executive has created an account on Twitter, after which it becomes one. We include executive characteristics in the model such as the age of the executive (*Executive age*), as the more frequent presence of younger individuals on social media is well documented.[2] We further include executive gender (*Female*), as women have generally been more likely to use social networking websites (though this phenomenon is historically weaker on Twitter).[3] Furthermore, as executives' personalities are likely related to their use of social media and Twitter in particular, we include executive extraversion (*Extraversion* and *Extraversion Missing*), as extraverted individuals are more likely to seek out attention, which a social media platform like Twitter can provide.[4] We construct the executive personality measures based on the Q&A sessions of the Refinitiv Street Events conference call transcripts. Using a mixed fuzzy and manual match to merge the conference call participants with executives in Execucomp by company ticker symbol, year, and name, we match 64% of all executives in our sample, including 62% of the executives who joined Twitter. Following Green et al. (2019), we use the Support Vector Machine (SVM) with linear kernel model from the Java program developed by Mairesse et al. (2007) to classify the personality of each executive at the Q&A level. The model simultaneously computes all Big-5 personality traits (extraversion, agreeableness, openness, conscientiousness, and emotional stability) for each executive-Q&A pair. For any executive with discussion in multiple conference

[2] For instance, Pew Research Center (2018) shows that, in the US, 45% of 18–24-year-old individuals used Twitter as of January 2018, dropping monotonically with age until the 50+ age group at 14% usage.
[3] Pew Research Center (2015) shows that back in 2010, among internet users, 68% of women vs. 53% of men used social networking sites. On Twitter in 2015, however, there was no statistically significant difference in gender dispersion on Twitter.
[4] Our results are robust to the inclusion of all Big-5 personality traits. We only include extraversion in our base model for parsimony.

call Q&As, we average their personality traits across the calls, treating the personality traits as constants per executive. As we use executive personality as a control variable, we replace any missing personality observations with the sample mean, and we also control for this replacement by including an indicator for the replacement in the regression (*Extraversion Missing*).

To control for regulatory changes, we include an indicator for whether the quarter occurs after the SEC Report in April 2013 that made explicit the SEC's open stance on executive social media usage (*SEC Regulation*). We also include various financial variables used in the prior literature, including firm size (*Size*), return on assets (*ROA*), market to book ratio (*MTB*), debt to assets ratio (*Debt*), and the Kim and Skinner (2012) litigation risk measure (*Litigation risk*). To control for any potential links between firms' Twitter activities and executives joining Twitter, we also include multiple measures related to firm tweeting activities: if the firm is on Twitter (*Joined Twitter, Firm*), the number of years since the firm joined Twitter (*Years since firm joined*), the number of followers the firm has (*log(Followers, Firm)*), the number of accounts the firm is following (*log(Following, Firm)*), and the total number of tweets the firm has posted over time (*log(Total tweets, Firm)*). We include industry fixed effects (GICS sector) as executives in more high-tech industries are likely to be more aware of Twitter, and we include year fixed effects to capture the natural time trend of users joining Twitter as the service itself expanded. All variables in the regression are defined in Table OA6.1.

Quarterly univariate statistics

Table OA6.2 presents the univariate statistics of independent variables used for our determinants of joining Twitter model. The table reports statistics separately for executive-quarters where executives are and are not on Twitter and tests the difference in means for each independent variable. Regarding executive characteristics, we see that all three characteristics are significantly different for executives on Twitter. Consistent with Pew Research Center (2018), younger executives are more likely to be on Twitter, with executives on Twitter being 2.2 years younger than those not on Twitter, on average. We also find that female executives are 22% more likely to be on Twitter than male executives. Lastly, as expected, we find that extraverted CEOs are more likely to be on Twitter.

Regarding the indicator for whether the quarter is after the SEC report greenlighting executive Twitter usage in 2013, the difference is quite large in favor of the post period; however, this cannot be distinguished from the general trend of users joining Twitter. Among firm characteristics, executives on Twitter are more likely to work for more growth-oriented firms, having higher market to book ratios. Furthermore, the firms whose executives are on Twitter tend to be smaller, less profitable, with less debt, and with higher litigation risk. Executives are also more likely to be on Twitter if the executive's firm has a Twitter account, as well as if the firm's account is more active (in terms of the number of followers, accounts it is following, and total tweets posted).

Panel B further explores the relationship between firms and their executives being on Twitter, showing a two-by-two split of this sample, across all quarter-level observations. When the firm is not on Twitter, its executive is on Twitter only 5.8% of the time, whereas if the firm is on Twitter the conditional probability that the executive is on Twitter is 8.5%.

Determinants model results

Table OA6.3 presents three different versions of the determinants model. Column 1 only includes the 2013 SEC report indicator, financial controls, and fixed effects (industry and year). We observe a marginally significant increase in executives on Twitter following the 2013 SEC report, and we observe a strong statistically significant effect for each financial variable in the model. Firm size and ROA both have a negative effect on the likelihood of an executive joining Twitter, while the market to book ratio, debt ratio, and litigation risk all have positive and significant associations with executives joining Twitter.[5]

Column 2 adds executive measures. Here, we observe that younger executives and female executives are more likely to be on Twitter, consistent with findings by Pew Research Center (2015, 2018) for the general population. We observe an impact of executive personality: more extraverted executives are

[5] In untabulated analyses, we additionally include an interaction between litigation risk and the 2013 SEC report. While all main effects remain the same across all model specifications, the interaction term has a significant negative coefficient. This indicates that while executives' likelihood of joining Twitter increases with litigation risk, the effect weakens after the 2013 SEC report.

more likely to be on Twitter, consistent with more extraverted individuals being more interested in seeking out attention.[6]

Column 3 adds firm Twitter account controls. While these may be endogenously related to the presence of executive Twitter accounts, as executives may highlight the firm account on Twitter, they can also serve as important determinants of the likelihood that the executive becomes aware of Twitter as a relevant dissemination channel. When we add in these controls, we see that all executive effects are robust, as is the impact of the 2013 SEC report; however, some financial controls (market to book ratio and debt ratio) lose significance.

Lastly, examining the untabulated industry fixed effects reveals that executives in the information technology industry (*t=7.87)* and the communications industry (*t=11.32*) are the most likely to join Twitter, likely due to the high-tech nature of the industries. Examining the untabulated year fixed effects, we note that all years from 2012 through 2018 have positive and significant effects, and that the magnitude of the effect is monotonically increasing, consistent with more executives joining over time.

For robustness, we have also run the determinants models of an executive having at least one, ten, or one hundred tweets. Results from these determinants models are generally consistent with the results from the tabulated determinants model, except that the April 2013 SEC report indicator drops significance.

[6] In untabulated robustness checks we find that these results are robust to adding the remaining four Big-5 personality traits to the regression. Both stability and conscientiousness are statistically significant and negatively related to executives joining Twitter, while agreeableness and openness are statistically significant and positively related to executives joining Twitter.

Table OA6.1: Variable definitions for determinants model

Variable	**Definition**
Dependent variable	
Joined Twitter, Executive	An indicator for whether the executive has opened a Twitter account by the given date. [Twitter API]
Determinants	
Executive age	Age of the executive, in years. [Execucomp]
Extraversion	Extraversion measured following Green et al. (2019) using conference call transcript Q&As. [Refinitiv StreetEvents]
Extraversion missing	An indicator for whether the executive was involved in too few conference calls to calculate *Extraversion*. [Refinitiv StreetEvents]
Female	Indicator for whether the executive is female. [Execucomp]
SEC Regulation	Indicator for whether the date is at or later than April 2, 2013, else zero.
Control variables (financial)	
Debt	Debt as a portion of assets, calculated as total liabilities (ltq) divided by total assets (atq), winsorized at 5% and 95%. [Compustat]
Litigation Risk	Litigation risk measured following Kim and Skinner (2012), updated yearly, and scaled linearly such that the lowest risk firm measures zero and the highest risk firm measures one. [Compustat & CRSP]
MTB	Market to book value, calculated as market value (mkvaltq) divided by total assets (atq), winsorized at 5% and 95%. [Compustat]
ROA	Return on assets, calculated as Net income (niq) divided by total assets (atq), winsorized at 5% and 95%. [Compustat]
Size	Log of assets (atq), winsorized at 5% and 95%. [Compustat]
Control variables (Twitter)	Note: The control variables *log(Followers, Firm)* and *log(Following, Firm)* are backfilled from the time of collection as historic data is unavailable from our data sources. Firm data is first available as of January 2017. For accounts that joined after September 2016, all controls are backfilled based on data collected in June 2021. For days missing these measures after the first date of availability, the previous non-missing observation is used.
Joined Twitter, Firm	An indicator for whether the firm associated with the executive has joined Twitter. [Twitter API]
log(Followers, Firm)	The log of one plus the number of Twitter accounts following the firm on Twitter. [Twitter API]
log(Following, Firm)	The log of one plus the number of Twitter accounts the firm follows on Twitter. [Twitter API]
log(Total tweets, Firm)	The log of one plus the number of tweets that the firm has posted up to the given date. [Twitter API]
Years since firm joined	If the firm has joined Twitter, then this measure equals the number of days since the firm joined Twitter divided by 365, else zero. [Twitter API]

Online Table OA6.2: Univariate statistics, quarterly sample of all executives, 2011 through 2018
Panel A: Univariate statistics split on if executive is on Twitter

	Executive on Twitter		Executive not on Twitter		On Twitter minus not on Twitter	
Variables	**Mean**	**S.D.**	**Mean**	**S.D.**	**Difference**	**t-stat**
Executive age	52.2	6.95	54.4	7.34	-2.18***	-25.3
Female	0.089	0.284	0.073	0.260	0.015***	4.96
Extraversion	4.01	0.523	3.90	0.509	0.107***	17.83
Extraversion missing	0.287	0.452	0.254	0.435	0.033***	6.46
SEC Regulation	0.866	0.341	0.668	0.471	0.197***	36.1
Size	7.73	1.78	8.13	1.72	-0.406***	-19.9
ROA	0.008	0.033	0.010	0.029	-0.002***	-5.09
MTB	1.66	1.70	1.35	1.37	0.307***	18.6
Debt	0.557	0.250	0.575	0.248	-0.019***	-6.38
Litigation risk	0.560	0.123	0.517	0.120	0.043***	30.4
Joined Twitter, Firm	0.758	0.428	0.681	0.466	0.077***	14.1
Years since firm joined	4.50	3.37	3.16	2.99	1.34***	37.6
log(Followers, Firm)	6.66	4.80	5.17	4.61	1.48***	27.2
log(Following, Firm)	4.70	3.37	3.64	3.35	1.05***	26.6
log(Total tweets, Firm)	5.46	3.93	4.08	3.78	1.38***	30.8
Observations	**7,727**		**101,620**			

Panel B: Executive Twitter account status by firm Twitter account status across all years

	Executive not on Twitter	**Executive on Twitter**	**Total**
Firm not on Twitter	29.7%	1.71%	31.4%
	(32,441)	(1,871)	(34,312)
Firm on Twitter	63.3%	5.36%	68.6%
	(69,179)	(5,856)	(75,035)
Total	92.9%	7.07%	100%
	(101,620)	(7,727)	(109,347)

Note: Panel A presents univariate statistics of the sample of executive-quarters from 2011 through the end of 2018. The first four columns describe the means and standard deviations for the sample of quarterly observations where the executive is or is not on Twitter. The fifth column shows the differences between executives on Twitter and executives not on Twitter, while the sixth column shows the difference *t*-statistics. Significance is denoted as follows: *** denotes $p < 0.01$, ** denotes $p < 0.05$, and * denotes $p < 0.10$. Panel B presents a two-by-two split on executives and firms having Twitter accounts, showing the percentage of observations that fall into each of the four cells.

Online Table OA6.3: Executives joining Twitter, determinants model

Variables	(1)	(2)	(3)
Executive age		-0.048***	-0.048***
		(-27.54)	(-27.23)
Female		0.135***	0.107**
		(3.10)	(2.44)
Extraversion		0.630***	0.600***
		(23.54)	(22.35)
Extraversion missing		0.082***	0.095***
		(2.91)	(3.28)
Post SEC	0.138*	0.150*	0.147*
	(1.69)	(1.83)	(1.78)
Size	-0.097***	-0.137***	-0.185***
	(-10.54)	(-14.15)	(-17.64)
ROA	-1.193***	-1.148***	-0.888**
	(-3.28)	(-3.12)	(-2.38)
MTB	0.027***	0.016*	-0.012
	(3.10)	(1.80)	(-1.32)
Debt	0.148***	0.087*	0.046
	(2.90)	(1.70)	(0.89)
Litigation risk	1.386***	1.092***	0.845***
	(10.26)	(8.03)	(6.15)
log(Followers, Firm)			0.074***
			(7.80)
log(Following, Firm)			0.041***
			(3.99)
log(Total tweets, Firm)			-0.048***
			(-3.97)
Years since firm joined			0.038***
			(4.55)
Joined Twitter, Firm			-0.581***
			(-10.49)
Constant	-4.090***	-3.680***	-2.940***
	(-29.92)	(-20.22)	(-15.60)
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Pseudo R-sq	0.074	0.096	0.100
Sample Size	109,347	109,347	109,347

Note: This table presents the results of regression equation (OA1) on the fiscal quarter sample of executives using a logistic regression model. Z statistics are presented in parentheses, and significance is denoted as follows: *** denotes $p < 0.01$, ** denotes $p < 0.05$, and * denotes $p < 0.10$.

Online Appendix OA7: Executive Tweet Posting Around Firm Events

Univariate analysis of executive tweets around earnings announcements and conference calls

To illustrate how executives post around earnings events, we present intraday distributions of tweet counts with respect to earnings announcements and earnings conference calls in Figure OA7.1. The top panels of Figure OA7.1 show results for earnings announcements. Both firms and executives increase their posting of financial tweets immediately after the earnings announcements, with the bulk of their financial tweets coming between the earnings announcement and the opening of the next trading day. However, while executives post around four times more financial tweets than usual during that period, firms post around 15 times more financial tweets than usual. The bottom half of Figure OA7.1 presents results for earnings conference calls. There is an uptick in posting financial tweets both right before and right after the earnings call. In contrast to our results for earnings announcements, executives post comparatively more financial tweets than firms do around earnings calls. Overall, we find that executives post more around earnings conference calls, while firms post around earnings announcements.

Multivariate analysis of executive tweets around firm events

In this analysis, we examine whether executive tweets might capture information that is useful for investors. If executives tweet in conjunction with firm events, they may provide useful information or perspective on the events. We thus explore how major corporate events and filings change the frequency of executives' *financial*, *non-financial business*, and *other* tweets. If the events coincide with other major news, we might observe an increase in *non-financial business* or *other* posts by executives. Otherwise, we would only expect to see an increase in *financial* tweets since the events we look at are primarily financial in nature.

To examine tweet counts, we adopt Poisson pseudo maximum likelihood (PPML) regression with clustered standard errors (by trading day) and high-dimensional fixed effects (HDFE), as implemented in

Correia et al. (2020).[7] Poisson regression is needed to model our dependent variables as they are count based; see Cohn et al. (2022) for a comparison of ways to model count data in accounting and finance applications. The implementation we use, PPML regression, is interpretable similarly to Poisson regression,[8] with the added benefits of being able to reliably use large amounts of fixed effects and being robust to sparse dependent variables (i.e., dependent variables that are mostly 0). Our main regression specification is:

$$\begin{gathered}[Topic]\ tweets, Executive_{t,p,e} = \alpha + \beta_1 Event_{t,f} + \beta_2\ [Topic]\ tweets, Firm_{t,p,f} + \\ \beta_3 Executive\ age_{t,e} + \beta_{\{4\text{-}7\}} Firm\ controls_{t,f} + \beta_{\{8\text{-}13\}} Twitter\ controls_{t,e,f} + \\ FE(Firm, Exec, Year, Month) + \varepsilon_{t,p,f,e}.\end{gathered} \tag{OA2}$$

Our dependent variable in these regressions is the number of tweets in a certain category, the category being denoted by [*Topic*] in the equation. The categories match the classification model in the paper, focusing on *Financial*, *Non-fin business*, and *Other* tweets. To get a more fine-grained understanding of when executives tweet in relation to events, we rerun each regression for three periods, p, of tweets: before trading, during trading, and after trading. *Event* is a count variable indicates the number events occurring for the executive's firm on the trading day: earnings events (earnings calls and earnings announcements), 10-K and 10-Q filings, or 8-K filings. The coefficient on *Event* represents the increase or decrease in tweets as compared to non-event days. The variable [*Topic*] *Tweets, Firm* controls directly for tweets by the executive's firm on the same topic and during the same window as [*Topic*] *Tweets, Executive*. This controls for the possibility that the executive is simply responding to firm dissemination or disclosure as opposed to the events themselves. For executive characteristics, we retain executive age and control for other factors using an executive fixed effect. For financial controls, we include firm size (*Size*), return on assets (*ROA*), market to book ratio (*MTB*), and debt to assets ratio (*Debt*). We also include Twitter controls

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[7] The authors of Correia et al. (2020) have made their work publicly available for Stata on SSC via the ppmlhdfe package. PPML as an estimator for count distributions has older roots in econometrics (Gourieroux et al. 1984), and this has been used by Call et al. (2018) in the accounting literature. The implementation we use, ppmlhdfe, differs from this past literature by allowing for high-dimensional fixed effects.

[8] Coefficients of the PPML regressions are log-scale like with Poisson regression. As such, an easy interpretation of a coefficient β_i is that e^{β_i} is the incidence rate ratio (IRR). The IRR is multiplicative; for instance, an IRR of 1.5 indicates that a change in the variable for the coefficient β_i of 1 leads to a 50% (1.5 – 1) increase in the dependent variable, all else held constant.

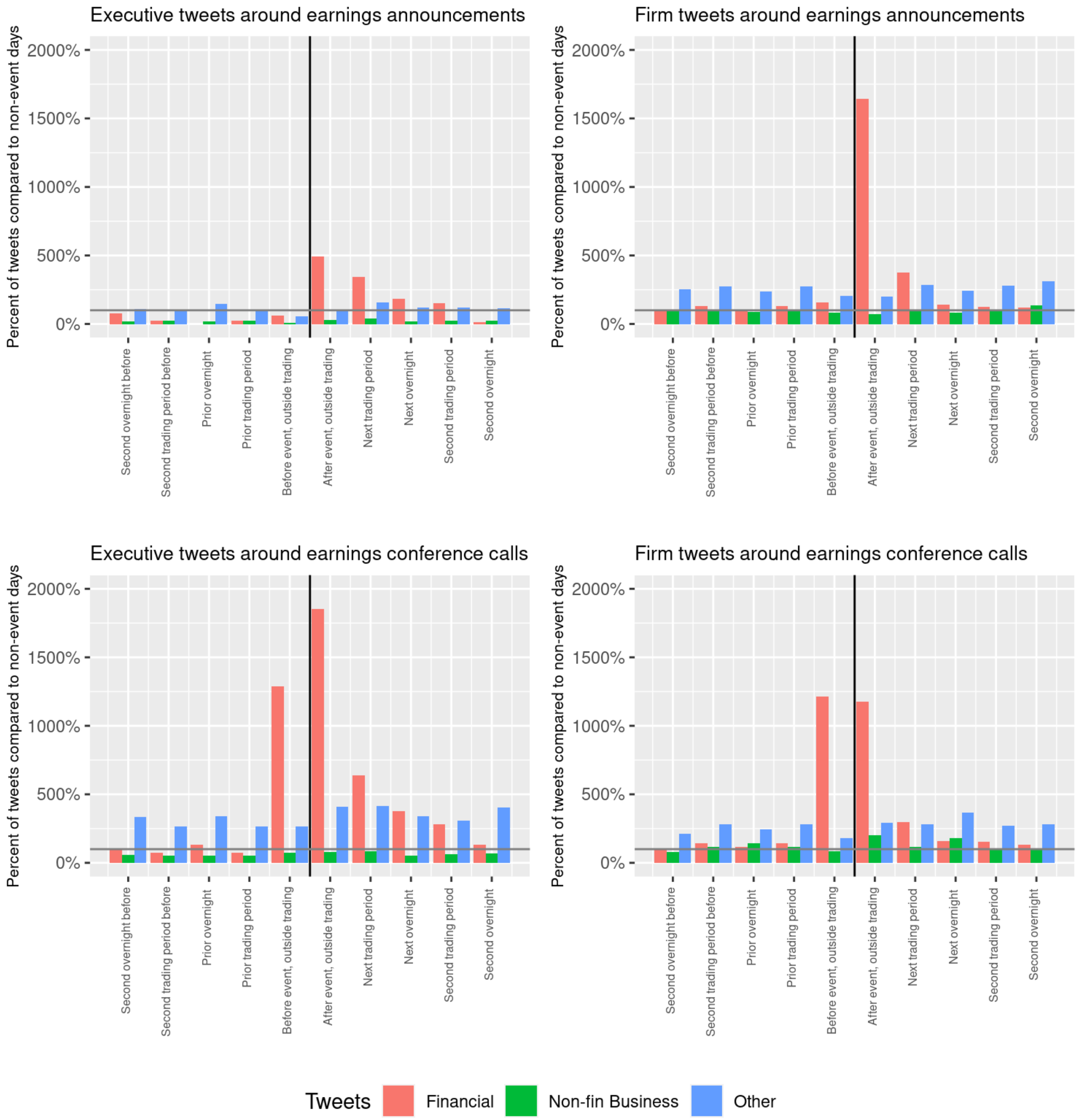
for firms, including the firm's number of followers (*log(Followers, Firm)*), the number of accounts it follows (*log(Following, Firm)*), and the total number of tweets posted up to the given day (*log(Total tweets, Firm)*). We augment these Twitter controls by including the same measures for the executives' Twitter accounts as well. Lastly, we include a comprehensive collection of fixed effects: firm, executive (which differentiates between CEO and CFO within firm), as well as year and month to capture any linear time trends in tweeting behavior.

Table OA7.1 Panel A presents the results examining the impact of earnings announcements and earnings conference calls on executive tweets.[9] We observe a large increase in the number of financial tweets posted around these events, and this increase occurs during the pre-trading period on the day of announcement, during trading, as well as overnight after the event has passed. As such, executives appear to use Twitter to disseminate financial information around earnings events for their firm. For tweets about non-financial (other) matters we do see a significant uptick, but this is much smaller in magnitude as compared to the impact on financial tweets, and it is concentrated during and before (only during) the trading hours of the day of announcement.

Table OA7.1 Panel B presents results for 10-K and 10-Q filings. 10-K and 10-Q filings also lead to an increase in executives posting financial information on Twitter. We do not observe an increase in non-financial business or other executive tweets during the trading day. The increase in financial tweeting again occurs across all three examined windows. Panel C presents results for 8-K filings. The results are similar to those for earnings events, except that the posting of non-financial business and other executive tweets is more concentrated in the period after the trading session instead of before it. Taking the results of all three panels together, we see strong support for executives timing their tweets, especially financial tweets. Overall, the findings in Table OA7.1 show that executives time their tweets and their tweeting behavior responds to a wide variety of financial information events.

[9] Earnings announcements and earnings conference calls occur on the same trading day over 80% of the time. Our results are robust when separately examining the impact of the two events.

Figure OA7.1: Tweets around earnings events, intraday



Note: This figure shows the relative number of tweets on different topics (financial, non-fin business, and other) by executives around earnings announcements and conference calls that occurred outside of trading hours. Tweet quantities in each window are normalized based on the average number of tweets of each type posted by executives on non-event days (outside of any [-2, +2] interval around either event type) during trading hours (for "During trading" panels) and outside trading hours (for "Outside trading" panels). For periods split by trading types, normalization is done assuming that the average event time is in the middle of the period. The grey horizontal line on each panel is at 100%; any bars above this represent extra tweeting beyond the usual non-event level. The vertical black bar represents when the event happened.

Table OA7.1: Executive response on Twitter to information events

Tweet period	**Financial tweets, Executive** (1)	**Non-fin business tweets, Executive** (2)	**Other tweets, Executive** (3)
Panel A: Earnings events			
Before trading	2.56***	0.196**	-0.088
	(7.47)	(2.36)	(-0.50)
During trading	2.17***	0.248***	0.248**
	(7.39)	(2.73)	(2.56)
After trading	1.18***	-0.112	-0.017
	(4.59)	(-1.09)	(-0.19)
Panel B: 10-K or 10-Q filings			
Before trading	1.83***	0.103	0.075
	(4.97)	(0.99)	(1.52)
During trading	1.91***	0.099	0.043
	(4.62)	(0.83)	(0.32)
After trading	1.09***	0.031	-0.074
	(5.34)	(0.28)	(-0.48)
Panel C: 8-K filings			
Before trading	0.915***	0.073	0.029
	(3.88)	(1.47)	(0.93)
During trading	0.979***	0.089*	0.075
	(3.26)	(1.77)	(1.43)
After trading	1.24***	0.107***	0.133***
	(5.00)	(2.74)	(2.67)

Note: This table presents the results of regression equation (OA2) on the regression sample using Poisson pseudo maximum likelihood (PPML) regression. Each cell represents the outcome of a separate regression. The dependent variable in each regression is the number of tweets posted by a manager during a given period, where column 1 examines counts of executive financial tweets, column 2 examines counts of executive non-financial business tweets, and column 3 examines counts of executive other tweets. Events occur between the close of the trading day prior to the observation and the close of the observation's trading day. Tweets are grouped into *before trading* (prior trading day close through current trading day open), *during trading* (open to close of current trading day), and *after trading* (current trading day close through next trading day open) windows. Each cell shows the coefficient on the indicator variable for the event of interest (earnings announcements and earnings conference calls, 10-K or 10-Q filings, and 8-K filings) for the given tweet type run in a separate regression, where the control group is comprised of non-event days. We use PPML regression including all controls along with fixed effects for Firm, Executive, Year, and Month. All standard errors are clustered by trading day and executive. Z statistics are presented in parentheses, and significance is denoted as follows: *** denotes $p < 0.01$, ** denotes $p < 0.05$, and * denotes $p < 0.10$.

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