12-2021

Executive tweets

Richard M.CROWLEY
Singapore Management University, rcrowley@smu.edu.sg

Wenli HUANG
Hong Kong Polytechnic University

Hai LU
University of Toronto

Executive Tweets

Richard M. Crowley
Assistant Professor of Accounting
Singapore Management University
rcrowley@smu.edu.sg

Wenli Huang
Assistant Professor of Accounting
Hong Kong Polytechnic University
wenli.huang@cpce-polyu.edu.hk

Hai Lu
Professor of Accounting
University of Toronto and Peking University
Hai.Lu@Rotman.Utoronto.Ca

This draft: October 5, 2022

We gratefully acknowledge the helpful suggestions of Elizabeth Blankespoor, Christian Leuz, Paul Koch, Ties de Kok, Ed deHaan, Sunghan Lee, Dawn Matsumoto, Xiumin Martin, Khim Kelly and the seminar participants of Carnegie Mellon University, Iowa State University, Rutgers University, Singapore Management University, University of Central Florida, University of Chicago, and University of Washington and the participants at the Humboldt University IRTG 1792 Summer Camp. This research is supported by the Hong Kong General Research Fund. Lu acknowledges the support from the McCutcheon Professorship in International Business at the University of Toronto.

Executive Tweets

Abstract

We explore the tweeting behavior of S&P 1500 firms' executives (CEOs and CFOs) and its market consequences during the period of 2011 to 2018. We document that executives tweet financial information related to their firms and time these tweets to firms' major events, and that investors respond to executive tweets in addition to firm tweets. Using the latest machine learning techniques, we develop an innovative construct measuring the content similarity between executive tweets and firm tweets. We use this measure to disentangle whether the market reaction comes from *new information* or *trust*. Consistent with the view from social identity theory that investor reaction is also driven by trust, we find that investors react more to information from executive Twitter accounts that is more content-wise similar to information already posted by firm Twitter accounts. In addition, we document that in the absence of firm disclosure, the market reacts to information content in the tweets by executives.

***Keywords*:** Social media; executives; dissemination; Twitter; social bond
***JEL Codes*:** G14; M12; M15; M40

Executive Tweets

1 Introduction

Social media is becoming central to the way in which individuals and corporations exchange information, with Twitter alone having 211 million active users per day.[1] Well-known executives like Richard Branson (Virgin), Tim Cook (Apple), Aaron Levie (Box), Elon Musk (Tesla, SpaceX), and Satya Nadella (Microsoft) have millions of followers each on Twitter. Social media posts from these high-profile corporate executives significantly affect the perception of investors on firm performance and move the market. A number of recent studies examine whether firms strategically disseminate information on Twitter and how the market responds to firm tweets (e.g., Blankespoor et al. 2014; Lee et al. 2015; Bartov et al. 2018; Jung et al. 2018; Crowley et al. 2022; Nekrasov et al. 2021). However, few empirical studies examine executive tweeting behavior even though individual Twitter accounts have become more popular and gained visibility. In this study, we fill this gap in the literature by examining executive tweets and their market impact. Specifically, we ask three research questions: Do executives consider Twitter as an important information channel to disseminate corporate news? Do executive tweets have an impact on stock price movements? If so, what is the mechanism through which executive tweets move the market?

To answer these questions, we collected all corporate and executive (CEO and CFO) tweets from S&P 1500 firms from 2011 through 2018.[2] Our final sample consists of 22.3 million tweets from 1,560 firms and 228 thousand tweets from 566 executives. In the final year of our sample, we find 451 executives on Twitter, with the total market capitalization of firms with executives on Twitter amounting to $7.5 trillion, or 29% of the market capitalization of our sample in that year. We use an unsupervised machine learning approach to process the large dataset and classify executive tweets into three categories—financial, non-financial business, and other tweets (Zhao et al. 2011). We randomly choose 500 tweets from each category to manually validate the classification by the algorithm and find that the consistency between manual and

[1] As of Q3 2021, per Twitter's 2021 Q3 letter to shareholders.
[2] We use the word "executive" throughout this study to refer exclusively to CEOs and CFOs.

machine classifications is high at 70%. In empirical tests, we focus on the class of financial tweets, as it is expected to have a direct impact on firm valuation and price movements in the market. In addition, taking advantage of a new algorithm developed at Google, Universal Sentence Encoder (Cer et al. 2018), we construct a similarity measure which compares the meaning of executive and firm tweets. We use the new measure as a proxy for new information in executive tweets relative to what has already been released in firm tweets, where a high (low) similarity score indicates less (more) new information in executive tweets.

Our first question is exploratory in nature. Firm and executive Twitter accounts are different. While the former is expected to primarily contain business related tweets, the latter could be exclusively devoted to personal use. The U.S. Securities and Exchange Commission (SEC) clarified on April 2nd, 2013, that both firms and executives are "public enough" so that information dissemination activity on their social media accounts should be in compliance with Regulation Fair disclosure requirements. However, whether executives would consider Twitter as an important information dissemination channel for corporate news is unclear. Unlike firm accounts that are likely to filter the information content to be posted, executives are more flexible in choosing content to tweet through their personal accounts. Their tweets may cover topics on politics, economy, climate, humanitarian subjects, or even hobbies. Many executives rarely tweet even if they have Twitter accounts, nor do they follow certain timing patterns. For example, Elon Musk's unjustified tweet about taking Tesla private on August 8, 2018, was posted at 12:48 AM and was unrelated to other corporate disclosure events.

Our findings show that there is a steady increase in the number of executives of S&P 1500 firms joining Twitter, from 3% in 2011 to 12% in 2018. The total number of tweets posted also increases. In addition, we find that executives who are active on Twitter post financial tweets when firms have major events include earnings announcements, earnings conference calls, 10-K and 10-Q filings, and 8-K filings. The evidence is consistent with the conjecture that executives consider Twitter as an important information dissemination channel.

Extending the existing research on the market consequences of information dissemination on social media, we develop and test two hypotheses. Our first hypothesis relates to the impact of executive tweets on stock returns. Prior studies show that broad information dissemination across multiple channels reduces the costs of awareness and acquisition, and thus improves market liquidity and price-responsiveness (see the review in Blankespoor et al. 2020). We hypothesize that executives' financial tweets impact stock prices.

Our second hypothesis relates to the mechanism through which executives' financial tweets impact the market. Specifically, we examine two mechanisms: *new information* and *trust*. On the one hand, executive tweets may not impact stock returns if they are only comprised of repetitive news that has already been disseminated on firm Twitter accounts. Such a scenario would suggest that investors do not distinguish between the source of the information on the same platform, namely the firm versus the executive. In this case, executive tweets may have an impact on stock returns if they contain incremental new information beyond those that have been released on firm Twitter accounts (i.e., *new information mechanism*). On the other hand, repetitive executive tweets may reduce the uncertainty of the signals perceived by investors and thus affect stock prices. Recent experimental studies based on social identity theory argue that investors develop social bonds when executives disclose information on Twitter and such social bonds influence investors' trust of the executives. This trust can then increase investors' trust of information disseminated by the executives (e.g., Elliott et al. 2018; Grant et al. 2018). Investors trust the CEO more and are more willing to invest in the firm when the CEO communicates firm news through a personal Twitter account (i.e., *trust mechanism*). Based on these experimental findings, we would expect that the market responds to executive tweets even in the absence of new content. The trust (new information) mechanism implies that the relation between executive tweets and stock returns is positively (negatively) affected by the degree of similarity between firm and executive tweets.

We find that stock prices react to both firm and executive tweets. On the day when executives tweet, stock prices react to executive tweets after controlling for firm tweets and corporate events. We further separate executive tweets into before-trading and during-trading samples. Our finding that the market responds to executive tweets posted before trading mitigates the endogeneity concern that executives may tweet after observing significant changes in stock price. In addition, we find the market does not respond to prior day firm or executive tweets.

In our tests disentangling new information and trust mechanisms, we show that the similarity between executive tweets and firm tweets positively affects the relation between executive tweets and market returns. That is, when executive and firm tweets are similar, investors react more strongly. The evidence is thus consistent with the trust mechanism for why investors respond to executive tweets although it does not rule out the new information mechanism. To provide a stronger test for the new information mechanism, we examine market reaction to executive tweets when the executive's firm has been silent on Twitter. We find that the market responds to executive tweets even when their firms were not tweeting. The evidence suggests these standalone executive tweets contain new information. Taken together, we conclude that empirical evidence supports both the trust and new information mechanisms.

Our paper contributes to the burgeoning research in finance and accounting on social media. Our paper is one of the first studies in the literature using a large sample to examine executive tweeting behavior and the market consequences of executive tweets. Despite the visibility and influence of individual tweets, the academic literature largely focuses on corporate Twitter accounts. Our paper differs from a concurrent working paper which also examines executive tweets (Chen et al. 2022). Chen et al. (2022) primarily shows a positive impact of executives Twitter presence on firms' information environment, with a focus on stock market liquidity and volatility. Our paper focuses on short-term (within a day) market response and examines the potential mechanism for the response. The samples of the two studies are significantly different. Chen et al. (2022) examines a set of 256 executives from 2008 to 2019, while our final sample includes 566 executives from 2011 to 2018.[3] In addition, the results from Chen et al. (2022) on stock price reaction are restricted only to negative discussion on "work-related day-to-day activities," showing an impact beyond the number of negative firm tweets about any topic. In contrast, we find a robust stock market reaction to executives' financial tweets against a strong baseline: firms' financial tweets. Our large

[3] Both Chen et al. (2022) and our study focus on CEOs and CFOs from S&P 1500 firms. However, we are able to identify more than twice as many executive Twitter accounts than Chen et al. (2022), although our sample period is slightly shorter. As both papers use Execucomp information to inform the collection process, the comprehensive nature of our collection process described in Section 3,1 leads to a more complete sample of executives on Twitter.

sample of executive and firm tweets requires and enables us to turn to the latest machine learning techniques to handle the data and develop innovative measures.

Our paper develops an innovative method measuring the similarity between firm and executive tweets and, as a result, provides new insights on how executives tweet and why investors respond. Specifically, executives appear to post financial tweets about their firms around the time when there are major corporate events. The market responds to executive tweets, but the response is largely due to the trust placed on these tweets. Our paper is the first study to develop a content similarity measure using Universal Sentence Encoder, one of the latest machine learning techniques, in a financial context. Taking advantage of the innovative measure, we are able to separate between the new information mechanism from the trust mechanism, providing large sample empirical evidence consistent with social identity theory and recent experimental findings (Elliott et al. 2018).

2 Literature and hypothesis development

2.1 Relevant literature

Social media has transformed the way firms engage with their customers, investors, and the market, inspiring related research in marketing, accounting, and finance. Of all social media outlets, Twitter is considered by many firms as their primary choice due to its "simple, social, short, and tangible" features (Colgan and Chow 2011). Jung et al. (2018) discusses the extent of Twitter use by firms as compared to other social media channels and finds that there are more S&P 1500 firms on Twitter than on all other examined platforms (Facebook, YouTube, LinkedIn, Google+, and Pinterest). Furthermore, it is commonly viewed that firms' Twitter followers are more likely to be present or potential investors while other outlets such as Facebook and LinkedIn are mainly used for social interaction or professional networking.

Examining investor behavior, a popular strand of literature focuses on predicting firm stock performance by leveraging content across users on Twitter. For instance, Sprenger et al. (2014) analyzes a set of 250,000 tweets related to S&P 100 firms over the span of six months and find that tweet sentiment appears to be associated with stock returns. Curtis et al. (2016) examines how investor response to earnings news is related to investors' activities on Twitter, finding a positive association between the two. More recently, Bartov et al. (2018) finds that information on Twitter helps predict both firm-level stock returns and future earnings.

More pointedly, another strand of research examines the extent to which firms disseminate information on Twitter as well as the consequences of such dissemination. Blankespoor et al. (2014) examines the impact of technology firms disseminating hyperlinks to earnings announcement press releases via Twitter. They find that this dissemination facilitates a decrease in information asymmetry. Lee et al. (2015) examines the context of consumer product recalls. They show that, during a recall, firms can limit the negative price reaction to the announcement of the recall by using social media. Jung et al. (2018) finds that firms are less likely to disseminate news when the news is bad and when the magnitude of the bad news is worse, consistent with strategic behavior. However, using a large sample of firm tweets in recent years, Crowley et al. (2022) finds no asymmetrical disclosures, i.e., firms disseminate more financial information on Twitter around major corporate events regardless of whether the information disclosed is positive or negative. Most recently, Nekrasov et al. (2021) shows that disclosure format on Twitter matters—including visuals in tweets significantly attracts the attention of investors.

Firm Twitter accounts are managed by firms' public relations teams and tweeting must follow corporate internal control procedures, whereas executive Twitter accounts are likely to be more flexible. Executives have more control over the content shared, but also shoulder more personal responsibility. As such, studying executive tweeting behavior is related to the emerging literature on firms' use of Twitter, but also presents a unique channel for dissemination with potentially different outcomes.

A separate strand of literature, which may inform why executives use Twitter, examines why individuals use Twitter. While Twitter first went online in 2006, as early as in 2007 it was documented that individuals were using Twitter to share and seek out information (Java et al. 2007). Toubia and Stephen (2013) provides an in-depth investigation of the motivations of users to contribute content to Twitter. They focus exclusively on non-commercial accounts on Twitter, and through a field study they document that users derive utility both intrinsically (directly through posting tweets) as well as through image-related effects (indirectly through the perception of themselves by others). Lin and Lu (2011) document an additional incentive for users to join Twitter: their peers. Using a questionnaire, they find that intrinsic utility is a driver of Twitter usage, but that the presence of individuals' peers on Twitter drives further intrinsic utility. Even if the motivations for having a Twitter account may be different across individual and firm accounts, an executive may post on Twitter for intrinsic or image-related benefits, or they may post on Twitter for company-related reasons. The decision of having a personal Twitter account is also related to age, gender, or executives' other personal features such as extraversion. However, to what extent executives would treat personal Twitter accounts as a corporate information dissemination channel remains unknown.

2.2 Hypothesis development

2.2.1 Executive Twitter accounts as an information dissemination channel

Executives may behave like any other individuals on Twitter, using the social media platform for their own personal enjoyment. Early surveys of executives suggest that the primary reasons executives are hesitant to adopt social media are that participating is risky and takes too much time, and additionally executives believe that disseminating information on social media has no measurable return on investment (Kwoh and Korn 2012; Weber Shandwick 2014). The resistance to use personal social media accounts to disseminate information, however, may also suggest that executives are concerned about the potential legal consequences of their posting behaviors. For example, on April 2, 2013, the SEC released the report titled "Report of Investigation Pursuant to Section 21(a) of the Securities Exchange Act of 1934: Netflix, Inc., and Reed Hastings." The SEC investigated a post by Reed Hasting on July 3, 2012,[4] to examine if 1) posting investor-relevant information via an executive's social media account is a violation of Regulation Fair Disclosure, and 2) if the SEC's August 2008 "Guidance on the Use of Company Web Sites" is applicable to social media platforms. The SEC concluded that the 2008 SEC guidance is applicable and that executives posting investor-relevant information on social media *is not* a violation of Reg FD.

[4] "Congrats to Ted Sarandos, and his amazing content licensing team. Netflix monthly viewing exceeded 1 billion hours for the first time ever in June. When House of Cards and Arrested Development debut, we'll blow these records away. Keep going, Ted, we need even more!" 2:57 PM UTC, July 7, 2012, https://www.facebook.com/reed1960/posts/10150955446914584.

Since the SEC report mitigated legal concerns associated with individual tweeting activity, it is expected to see an increase in executives joining Twitter as the interactive nature of the social media platform would allow for a convenient channel to disseminate corporate information. Moreover, if executives tweet for intrinsic utility or due to the pressure of peers on Twitter, they should be less likely to post investor-relevant information on social media. To identify the content of executive tweets, we, thus, classify them into three categories – financial tweets, non-financial business tweets, and other tweets. We expect that executives would react to various corporate events when they occur by strategically timing their tweets. For instance, releasing of an earnings announcement, holding an earnings conference call, or releasing a 10-K or 10-Q filing should drive executives to post about financial information on Twitter. Likewise, the release of important documents with a broader focus such as 8-K filings should drive financial as well as broader business-related information dissemination on Twitter by executives. In contrast, if executives do not consider social media as an important information dissemination channel, we would expect their behavior on Twitter not to respond to major corporate events. How executives consider their individual Twitter accounts in relation to firm accounts is, thus, an empirical question.

2.2.2. Market Consequences of Executive Financial Tweets

It has been documented in the literature that firm tweets are informative to investors, such as firm tweets to press releases (Blankespoor et al. 2014) or firm tweets that are explicitly financial in nature (Jung et al. 2018.; Crowley et al. 2022; Nekrasov et al. 2021). There is also evidence showing that tweets posted by the public can predict market movements (Bollen et al. 2011), and that explicit discussion of stocks on Twitter by investors can predict market movements and earnings (Mao et al. 2012; Sprenger et al. 2014; Bartov et al. 2018). As most related studies examine explicit discussion of financial content on Twitter, we focus our hypotheses on financial tweets by executives.

As financial discussion by investors contains useful information, and as it would be natural to expect that posts by executives could contain more useful information than those by most investors, we expect that executives' financial tweets should be useful to the market. For example, social media posts such as that by Elon Musk in 2018 tweeting about taking Tesla private have been shown to influence the market. However, it is less clear if, when executive and firm financial tweets are posted together, whether executive financial tweets would be incrementally informative to investors beyond firm financial tweets. It is also possible that the information posted by executives is largely similar to what is already available elsewhere. As such, we might expect that there is no new information content in executive tweets which may dampen their effect on the market. Meanwhile, even if executives "play it safe" and avoid posting new disclosures on Twitter, the information may still be useful to investors, particularly when it comes to financial tweets. Given the existing evidence from prior literatures on the role of social media platforms in influencing investor perceptions and moving stock price, we, thus, state our first hypothesis as follows:

Hypothesis 1*: The market responds to executive financial tweets in addition to firm tweets.*

The market may respond to executive financial tweets for different reasons. Executive financial tweets may provide new information that is different from the information in firms' tweets (*new information mechanism*). Even if executive financial tweets do not provide new information, the tweets may enhance the trust investors have about the tweeted information, as social bonds between investors and executives on social media can facilitate such trust (*trust mechanism*). Social identity theory predicts that social bonds are developed when individuals personally interact with other individuals (such as on social media) and such bonds cause individuals to develop more trust in others (e.g., Lewicki and Bunker 1996; Elliott et al. 2018). Importantly, social bonds are likely weaker when individuals interact with a corporation rather than a person. Twitter provides an opportunity for Twitter account owners (executives) to develop social bonds with followers (investors), which should be stronger than investors' social bonds with executives' firms. These social bonds can facilitate investors' trust in executives, increasing investors' trust of information posted by executives on social media beyond the trust investors would place on a similar disclosure by firms. A recent experimental study indeed shows that investors trust CEOs more and are more willing to invest in a firm when the CEO disseminates firm news through a personal Twitter account than when the news comes from the firm's Twitter account or website (Elliott et al. 2018). The finding is consistent with the results from a survey of Fortune 500 employees in which eighty-two percent of survey respondents stated that they are more likely to trust a firm when the CEO engages with social media (Brandfog 2012). These findings suggest that the channel through which investors obtain information is important – the information remains unchanged but the uncertainty about the information perceived by investors changes.

To disentangle between the *new information* and the *trust mechanism*, we make use of the information content similarity between executive and firm tweets. The content similarity between an executive's financial tweet and their firm's tweets can capture a lack of new information. Whereas the *trust mechanism* is consistent with a positive relationship between stock return movement and the similarity of executives' financial tweets to their firms' tweets, the *new information mechanism* suggests a decreasing relationship. Accordingly, we state our two sets of hypotheses corresponding to each of the mechanisms as follows:

Hypothesis 2a (New Information Mechanism)*: The market responds more strongly to executive financial tweets with content that is more different from firm tweets.*

Hypothesis 2b (Trust Mechanism)*: The market responds more strongly to executive financial tweets when the tweets' content is more similar to firm tweets.*

We note, however, that the two hypotheses are not mutually exclusive – it is possible that investors both react to trust through social bonds and to new information posted by executives. To test if both occur together, we also include a stronger test of the *new information mechanism*: market reaction to financial tweets by executives when their firms have not tweeted in the period leading up to the executives' financial tweets. Such tweets are more likely to contain new information (at least within the dissemination channel of Twitter). We state this formally as follows:

Hypothesis 2c (New Information Mechanism)*: The market responds to executive financial tweets when the executive's firm did not tweet beforehand.*

3 Data and methodology

3.1 Data and sample selection

Our sample spans the years 2011 through 2018 and covers all S&P 1500 firms that were contained in the index between January 1, 2012, and December 31, 2018. Twitter handles for companies and CEOs were initially identified via hand collection between September and October 2016, while Twitter handles for CFOs were initially identified in April 2017. A subsequent round of hand collection was conducted in May 2020.[5] In total, we have identified 1,635 firm accounts and 621 executive accounts.[6] Our tweet sample is based on data from the Twitter API and from Gnip, a data provider and subsidiary of Twitter. Specifically, we used the Twitter API to download all publicly available tweets associated with each Twitter ID in October 2016.[7] Public access via the Twitter API is limited to the 3,200 most recent tweets per account, and as such 614 firm and 3 executive accounts had incomplete sets of tweets. For these companies and executives, we purchased a complete set of tweets from Gnip. We then collected 2017 and 2018 data by continuously downloading the data via the Twitter API. For data from our second collection exercise, we collected all tweets up to the most recent 3,200 from the Twitter API, and we collect any missing tweets beyond the 3,200 tweet limit using snscrape.[8]

Our financial data, executive data, and stock return data are from Compustat Fundamentals Quarterly, Execucomp, and CRSP, respectively. For identifying information events, we use the following sources: I/B/E/S for earnings announcement times, Capital IQ for earnings conference call times, and WRDS SEC Analytics Suite for 10-K, 10-Q, and 8-K times.

---

[5] We collect executive accounts through use of Twitter's search function, Google search, and LinkedIn profiles. We verify accounts are the executives' accounts by examining the user description and tweet content. For instance, we compare the executives' current position (as indicated on Execucomp or LinkedIn) to the information on the Twitter profile to ensure a correct match.

[6] We caveat that the hand collection of executive Twitter accounts requires the account to be identifiable to a user. As such, if an executive maintains an account that is anonymous (e.g., without any publicly identifiable information including name or position and company), then the account would not be captured in our hand collection exercise. However, it is unlikely that such an account would have an effect on financial markets since it would be anonymous.

[7] Twitter IDs act as a permanent identifier on Twitter. While most users are familiar with Twitter handles (usernames prefixed with "@" that are shown on Twitter), Twitter handles can easily be changed whenever a user decides to do so. Twitter IDs, however, remain the same when the associated Twitter handle changes. As such, collecting data by Twitter ID means that our collection is not impacted by changes in Twitter handles by firms or executives.

[8] The snscrape python library is available at https://github.com/JustAnotherArchivist/snscrape.

To calculate measures capturing executive personality traits, we follow Green et al. (2019) and examine conference call transcripts from Refinitiv Street Events from January 2001 through April 2019.

Our full sample consists of all firms, CEOs, and CFOs that were in the S&P 1500 any time between January 1, 2012, and December 31, 2018, where the firm has complete control variable information in Compustat, is in CRSP, and has a CEO, a CFO, or both in Execucomp. This sample is comprised of approximately 6.92 million (114,684) firm-executive-trading day (firm-executive-fiscal quarter) observations. With the above sample restrictions in place, our final sample of Twitter data includes approximately 228 thousand tweets from 566 executives, as well as 22.3 million tweets from 1,560 firms.

3.2 Measure construction

A key feature of our data is that nearly all the data (tweets and all information events) is tracked to the second of announcement. As such, we standardize all data by assigning each tweet or event to time periods based on NYSE trading days. We bifurcate each trading day into two time periods: *during trading* and *before trading*. If a tweet or event occurs on a trading day *t* and is released between the open of the stock market (9:30 AM in the Eastern Time Zone) and the close of the stock market (4:00 PM in the Eastern Time Zone), we assign it to the *during trading* period for day *t*. If the tweet or event occurs after the closing time on trading day *t-1* and before the opening time for trading day *t*, we assign it to the *before trading* period of day *t*. We also define a period *after trading*, which is the *before trading* period on day *t+1*. A timeline of these periods is illustrated in Figure 1. We adjust all timestamps for issues such as the time-zones that data are derived from (generally either the Eastern Time Zone or GMT) and daylight savings time.

3.2.1 Twitter measures

Our primary measures derived from our Twitter data are counts of the tweets posted by executives and firms in each period. Tweets are aggregated to the bifurcated trading day level as just described above. To measure the content of tweets, we use the Twitter-LDA algorithm by Zhao et al. (2011) to machine learn the content of tweets. Twitter-LDA itself is a modified version of the LDA algorithm to adjust for the short length of tweets, as short "documents" are a noted problem for LDA. LDA (Latent Dirichlet Allocation) is a machine learning algorithm by Blei et al. (2003) that classifies the thematic content (i.e., topics) of text in a Bayesian manner without any oversight from the researcher (i.e., LDA is an unsupervised algorithm). LDA has grown in popularity in the accounting literature, and has been used in numerous studies (see, e.g., Dyer et al. 2017; Huang et al. 2018; Brown et al. 2020).

We use the same Twitter-LDA model as used by and described in detail in Crowley et al. (2022). This model classifies tweets into 60 different machine-learned topics. We then cluster these 60 topics into three overarching categories of information: *financial*, *non-financial business*, and *other*. Financial tweets are likely to be the most informative, as financial information is crucial for evaluating firm performance and valuation. Non-financial business tweets are company-relevant tweets, covering topics such as business events, marketing, conference participation, and customer support, and thus may be of interest to investors. Other tweets are likely unrelated to the firm, and may be about day-to-day life, sports, travel, or other interests. To categorize a tweet, we determine which of the 60 topics of the Twitter-LDA model the tweet most relates to by applying the weighted dictionaries generated by Twitter-LDA to each tweet and picking the topic with the highest weight for each tweet. We map each tweet to a category based on its topic; examples of tweets from each category are provided in Appendix B.[9] For additional details on the construction of the topics, as well as examples of the most common words and bigrams from tweets in each category, see Appendix C. For daily analyses, we aggregate tweets by counting the number of tweets in each category on each trading day.

We validate the measure by manually coding 500 tweets from each of the three categories. We find an average agreement of 70% between manual coding and our algorithm. Importantly, we find minimal Type I error in our classification of financial tweets, with a sensitivity of 99%. We also find low Type II error for classifying financial tweets, with a specificity of 87.5%. Overall, our Twitter-LDA implementation performs well at classifying financial tweets. Appendix D provides more details on this validation exercise.

[9] The topics are hand classified based on a reading of the top 20 words in each topic. The *financial* category contains 1 topic, the *non-financial business* category contains 42 topics, and the *other* category contains 17 topics.

In our determinants of joining Twitter model, we use whether the executive has a Twitter account as of the beginning of a given quarter as the dependent variable. We also present results requiring executives to have tweeted, as we find that 160 of the 621 executives we identified never released a tweet publicly by the end of 2018.[10]

For control variables, we include the log of one plus the number of followers of each account, the log of one plus the number of accounts the executive or firm Twitter account is following, and the log of one plus the total number of tweets posted by the account to date. Of the control variables derived from Twitter data, followers and following are all left-censored measures, as Twitter provides these measures at the time the information is accessed, not historically. As such, for the executives and firms on Twitter in our initial collection, we have data throughout 2017 and 2018; for the accounts collected in our second collection exercise, we only have these figures as of July 1, 2021.[11] We backfill these measures using the closest data we have for the account.

For testing Hypothesis 2, we introduce a fine-grained measure of content or meaning of text to the accounting literature, called Universal Sentence Encoder (USE). The USE algorithm, developed by Cer et al. (2018) at Google, leverages neural networks to process text on the order of sentences or short paragraphs, factoring in word order. As such, this model breaks away from the typically bag-of-words-based approaches used in the accounting literature, such as dictionaries or LDA, allowing it to ascribe a more precise meaning to a sentence. Furthermore, the short nature of tweets means that we can encode whole tweets easily with USE. For our analysis we use a model pre-trained on a variety of online information sources, including "Wikipedia, web news, web question-answer pages and discussion forums" (Cer et al. 2018). Given that Twitter is likewise a source of general web content, we expect this model to transfer well to our context. The USE algorithm maps each tweet to a vector space where similar meanings are all mapped to the same

[10] There are three possible reasons for an account to exist but not have tweets. First, the executive may use Twitter only to acquire information, not to disseminate. Second, the executive may have deleted all public tweets before we scraped them from the Twitter API or acquired them from Gnip. Third, the executive may have set their account to private. Deleted posts and private posts cannot be acquired due to license restrictions, and thus we acknowledge that they are data limitations for this study.

[11] Unfortunately, historical data is unavailable for follower and following data via the Twitter API and Gnip.

local area. We leverage this feature to precisely measure the similarity of executive tweets with firm tweets. Examples of sentences encoded with this algorithm and their respective similarities are provided in Appendix E, along with a more detailed description of our methodology.

For each executive tweet we identify all tweets by the executive's firm in the two days leading up to the executive tweet, precisely up to the second prior to the executive tweet.[12] For matched executive tweets, we search for the closest firm tweet to the executive tweet.[13] After distances are calculated for each executive tweet, we compute *Tweet similarity* by normalizing the distance to the interval [0,1] and subtracting the normalized distance from one. We aggregate *Tweet similarity* by taking the mean across all an executive's tweets of a given type (e.g., financial tweets) throughout the before trading or during trading window. A higher *Tweet similarity* score indicates a tweet or set of tweets that is more consistent with the meaning of existing tweets by the executive's firm, whereas a lower score indicates tweets that are content-wise different from those of the executive's firm. In our tests, we also capture instances of executive tweets that do not have a corresponding firm tweet in the two-day window using an indicator variable, *No firm tweet*.

3.2.2 Executive personality measure

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 to 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

[12] In an untabulated robustness check we extend the window from two days to seven days before the executive's tweet. Our key results are unchanged by using a seven-day window. Our results are also robust to using a shortened window of just one day.

[13] We measure distance using Euclidean distance (L2 norm) and implement the Approximate Nearest Neighbor matching algorithm of Arya and Mount (1993) to efficiently compute exact matches between executive and firm tweets. In an untabulated robustness check we calculate distance using the L1 norm. Our results are unchanged using the L1 norm.

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 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.

3.2.3 Event measures

In our determinants of joining Twitter model, we include an indicator variable to capture the 2013 SEC report that greenlit executives to use Twitter for material disclosure. This report was released on Tuesday, April 2, 2013. To differentiate between observations before and after the SEC report, we construct a variable, *SEC Regulation*, equal to 1 for April 2, 2013, or later. In our quarterly tests, we code *SEC Regulation* as 1 if the quarter started after April 2, 2013.

The other events are all firm-level events, which we map to trading days. Using intraday timestamps from I/B/E/S data, we create a variable, *Earnings announcement*, equal to 1 if there is an annual or quarterly earnings announcement during trading or before trading, 0 otherwise. The second measure we create is *Earnings call*, which captures if there is an earnings conference call during trading or before trading, based on intraday timestamps from Capital IQ's conference call schedule. As earnings announcements and earnings conference calls overlap significantly (>80% are on the same trading days), in our Tables we present results using an aggregate measure of the two, which we call *Earnings events*. Our third measure captures releases of SEC filings. Using WRDS, we construct *10-K and 10-Q filing*, which has a value of 1 if there was a 10-K or 10-Q filing released on the given trading day. We also construct *8-K filings*, which captures the number of 8-K filings released on a given day.[14]

3.2.4 Return measures

Our primary return measures are based on market model return (MMR). We calculate betas using 3 months of lagged daily returns and S&P 500 returns. For tests involving stock returns, we present results

[14] We include this measure as a count as opposed to a binary measure, as we find that a non-trivial number of days with 8-K filings contain multiple filings (3.9%). In our sample, the most 8-Ks filed on the same trading day is 4.

using a precise window restricted to only day *t*.[15] When we use this alongside executives' tweeting behavior before trading opens, this eliminates any concern of reverse causality from executives tweeting due to stock price movements. While studies in accounting often use multi-day windows of (t – 1, t + 1) or (t, t + 1) to account for information leakage or expectations of investors about scheduled events, tweets by executives are not a type of disclosure that should be expected or that is mandatory, and thus we expect less leakage of their effect to prior days/times. For robustness, in untabulated analyses we also confirm our results using S&P 500 adjusted returns and raw returns.

4 Empirical methodology and results

4.1 Methodology

4.1.1 Determinants: Executive adoption of Twitter

To examine the determinants of executives joining Twitter, we use our quarterly sample as described in Section 3.1. We examine the determinants of executives joining Twitter using a logistic model:

$$\begin{gathered} Joined\ Twitter_{t,e} = \alpha + \beta_1 Executive\ characteristics_{t,e} + \beta_2 Post\ SEC_t + \\ \beta_3 Financial\ controls_{t,f} + \beta_4 Twitter\ controls_{t,f} + FE(Industry) + FE(Year) + \varepsilon_{t,f,e} \end{gathered} \quad (1)$$

Joined Twitter is our event of interest, and it is 0 until an executive has created an account on Twitter, after which it becomes 1. This serves as a determinants model to explain some of the variation in executives that did and did not join Twitter. As such, 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.[16] 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).[17]

[15] We have also run our return tests on intraday windows, looking at return in the 10, 30, or 60 minutes after a financial tweet by an executive. For this test, we obtain our intraday stock price data from TAQ. We discuss the results in Section 4.2.4. A caveat of this design is that only tweets during trading can be examined, since there is no intraday return defined for tweets posted outside trading hours. We do not find any statistically significant effects on these shortened windows.

[16] 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.

[17] 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.

Furthermore, as executives' personalities are likely related to their use of social media and Twitter in particular, we include executive extraversion (*Extraversion*), as extraverted individuals are more likely to seek out attention, which a social media platform like Twitter can provide.[18] To control for regulatory changes, we include an indicator for if the quarter occurs after the SEC Report in April 2013 that made explicit the SEC's open stance on executive social media usage. 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 days since the firm joined Twitter (*Days 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 (*Total tweets, Firm*). We include industry fixed effects (GICS sector) as executives at 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 Appendix A.

4.1.2 Importance of Twitter as an information dissemination channel for executives

Should executives view Twitter as an important information dissemination channel, we would expect to see an increase in tweeting, and in particular an increase in tweeting about financial information, around major corporate events and filings. We explore how major corporate events and filings changes 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 *other* discussion by executives (discussing the news), or a general increase in tweets across all categories (amplifying Twitter usage). However, should the executives view Twitter as an important channel for information dissemination, we would expect to see an

[18] Our results are robust to the inclusion of all Big-5 personality traits. We only include extraversion in our base model for parsimony.

increase in tweets in more business-relevant discussion, especially financial discussion since the events we look at are primarily financial in nature.

For these tests we restrict the sample to only executive-firm-day observations where *Joined Twitter, Executive* is 1, i.e., days where the executive has a Twitter account. To examine tweet counts, we adopt a new regression structure, Poisson pseudo maximum likelihood (PPML) regression with robust standard errors and high-dimensional fixed effects (HDFE), as implemented in Correia et al. (2019).[19] PPML regression is interpretable like Poisson regression,[20] 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:

$$\begin{gathered} Topic\ Tweets, Executive_{t,p,e} = \alpha + \beta_1 Event_{t,f} + \beta_2\ Topic\ Tweets, Firm_{t,p,f} + \\ \beta_3 Executive\ age_{t,e} + \beta_4 Financial\ controls_{t,f} + \beta_5 Twitter\ controls_{t,e,f} + \\ FE(Firm, Exec, Year, Month) + \varepsilon_{t,f,e} \end{gathered} \tag{2}$$

Our dependent variable in these regressions is the number of tweets in a certain category. To get a more fine-grained understanding of when executives tweet in relation to events, we rerun each regression for three windows of tweets: Before trading, during trading, and after trading. *Event* is an indicator or count variable that is one of the event measures discussed in Section 3.2.3 (*Earnings events*, *10-K and 10-Q filing*, *8-K filings*). The *Earnings events* measure covers the before trading and during trading windows, while the other two events match to the day of release or, for non-trading days, the next trading day after the event. 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, Exec*. This serves to control for the possibility that the manager 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

---

[19] The authors of Correia et al. (2019) 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, Monfort and Trognon 1984), and 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.

[20] 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.

executive fixed effect. For financial controls, we include firm size (*Size*), return on assets (*ROA*), market to book ratio (*MTB*), debt to assets ratio (*Debt*). We also include Twitter controls for firms, including if the firm is on Twitter (*Joined Twitter, Firm*), the firm's number of followers (*log(Followers, Firm)*) and following (*log(Following, Firm)*), and the total number of tweets posted up to the given day (*Total tweets, Firm*). We augment these Twitter controls by including the same measures for the executives' Twitter accounts as well (except for the *Joined Twitter* measure, which is always 1 for executives in this sample). 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.

4.1.3 Market reaction to executives' tweets (H1)

To address Hypothesis 1, we directly examine stock returns around executive tweets. We focus on absolute market model returns, as this has been used to reliably capture stock market reaction to disclosures with no *ex ante* known directional impact (e.g., Campbell et al. 2014; Hope et al. 2016). To test Hypothesis 1, we use a linear regression with HDFE and robust standard errors:[21]

$$\begin{aligned}|MMRet_{window}| = \alpha + \beta_1 Topic\ Tweets, Executive_{t,p,e} + \beta_2 Topic\ Tweets, Firm_{t,p,f} + \\ \beta_3 |MMRet_{t-1}|_{t,f} + \beta_4 Executive\ age_{t,e} + \beta_5 Financial\ controls_{t,f} + \\ \beta_6 Twitter\ controls_{t,e,f} + FE(Firm, Exec, Year, Month) + \varepsilon_{t,f,e}\end{aligned} \tag{3}$$

As our events are tracked intraday, we are able to examine the market response to tweets released at various times in relation to our trading day. In our primary test of Hypothesis 1, we examine the market reaction to tweets released during the same trading period (contemporaneous reaction) as well as tweets from the period before trading (i.e., from the previous trading day's close to the current day's open). In a secondary test, we condition and further split these windows based on when an earnings event occurred, into before and after earnings event sub-periods. For all tests of Hypothesis 1, our independent variable of interest is *Topic Tweets, Exec*, the number of tweets from our three categories (financial, non-financial business, other). For our independent variable, a positive and significant coefficient would be consistent

[21] We implement this regression model using reghdfe, available in the Stata SSC and described in Correia (2016).

with Hypothesis 1. As with our regression test on the importance of Twitter as a disclosure channel, we control for the tweet content of each executive's firm, the executive's age, financial controls, Twitter account controls for both the executive and firm, and a set of fixed effects including firm, executive, year, and month fixed effects. We additionally control for the prior day's absolute market model return.

4.1.4 Market response mechanism (H2)

To examine Hypothesis 2 and the mechanism underlying the market response to executive tweets, we use the same regression structure as for testing Hypothesis 1. We restrict the sample to only those firm-executive-day observations where both the executive and firm have Twitter accounts already, as our *Tweet Similarity* measure cannot be defined if either party does not have an account.[22] To test the mechanism, we include two additional measures into the equation (3): *Tweet similarity* and *No firm tweets*. We include the interaction of each of these two measures with *Financial tweets, Executive* as our primary measures of interest, and we include the main effect of Tweet similarity so as to fully interact it. We include an indicator, *Similarity undefined*, to control for all instances where our similarity measure is not calculable due to no executive financial tweets or no matching firm tweets. We use a linear regression with HDFE and robust standard errors as follows:

$$\begin{gathered}|MMRet_t| = \alpha + \beta_1 Financial\ tweets, Executive_{t,p,e} + \beta_2 Tweet\ similarity_{t,p,f,e} + \\ \beta_3 Tweet\ similarity_{t,p,f,e} \times Financial\ tweets, Executive_{t,p,e} + \\ \beta_4 Similarity\ undefined_{t,p,f,e} + \\ \beta_5 No\ firm\ tweets_{t,p,f,e} \times Financial\ tweets, Executive_{t,p,e} + \\ \beta_6 Financial\ tweets, Firm_{t,p,f} + \beta_7 |MMRet_{t-1}|_{t,f} + \beta_8 Executive\ age_{t,e} + \\ \beta_9 Financial\ controls_{t,f} + \beta_{10} Twitter\ controls_{t,e,f} + \\ FE(Firm, Exec, Year, Month) + \varepsilon_{t,f,e}\end{gathered} \tag{4}$$

The mechanism can be differentiated based on the sign of β_3. A positive and significant coefficient on this interaction would be consistent with Hypothesis 2b and would indicate that investors react more strongly when executives post financial tweets that are content-wise similar to tweets their firm has posted

[22] In untabulated tests we find that relaxing this restriction by including executives whose firms are not on Twitter (by setting *Tweet Similarity* to 0 for such observations) has no impact on our results.

over the prior two days.[23] As such, this would support the trust mechanism. Alternatively, a negative and significant interaction would be consistent with Hypothesis 2a. This would indicate that investors react more strongly when executives post financial content that is different from what the executive's firm has posted, which would support the new information mechanism.

However, we note that not every financial tweet by an executive can be matched to a corresponding tweet or set of tweets by the executive's firm, should the firm have remained silent on Twitter before the executive tweeted. In such cases, it is more likely that the executive's tweet may be acting as a primary source of information, in which case the new information mechanism may be stronger. Such a case would be consistent with Hypothesis 2c, and we would expect to see a positive and significant coefficient on β_5. It is possible that we would simultaneously observe both mechanisms, should both β_3 and β_5 be positive in the regression. In such a case, that would indicate that the role an executive plays on Twitter depends on the actions or disclosure strategy of the executive's firm. If the firm discloses information on Twitter, an executive can confirm the information and increase its reliability. On the other hand, if the firm chooses to not disclose on Twitter, then an executive can play an information role by being the first to release information on Twitter.

4.2 Results

4.2.1 Univariate analysis

Figure 2 presents statistics on our sample of Twitter accounts, subject to sample requirements of the executive's firm having complete control information for a given firm-year. Panel A presents the percentage of executives of S&P 1500 firms that have Twitter accounts in each year. Predictably, we find that the number of executives with Twitter accounts increases over time, starting at just 107 executives (2.6%) in 2011 and peaking at 451 executives (12.1%) in 2018. In terms of industries (not tabulated for brevity), we find that two industries, communication services and information technology, have the highest

[23] We compare executive financial tweets against all tweet types by firms. This ensures that, should any financial tweet by firms not be correctly classified as financial by our Twitter-LDA approach, we still use them as a relevant comparison.

proportion of executives on Twitter in the final year of our sample (2018), at 23.7% and 19.9%, respectively. The real estate industry has the lowest proportion of executives, 5.6%, on Twitter in 2018. In total, our sample of executives with Twitter accounts consists of 566 executives across 2,350 executive-firm-years. The second part of Panel A presents the total number of tweets by executives per year. We see a sustained increase in the number of tweets each year through 2017, along with a decrease in tweets in 2018. This decrease is likely attributable to the increased length of tweets allowed starting on November 7, 2017. In untabulated analyses, we examine the percent of aggregate market capitalization represented by firms with executives on Twitter. In 2011 this is only 4.8%, but by 2018 we find that 29% of the total market capitalization of the firms in our sample is represented by an executive on Twitter; these firms with executives on Twitter have an aggregate market capitalization of approximately $7.5 trillion. For the information technology and consumer discretionary industries the percent of total market capitalization by firms with executives on Twitter is substantial, at 62% and 47%, respectively.

Figure 2 Panel B presents the sample of firm Twitter accounts. As with the executive accounts, we find that communication services and information technology have the highest rate of adoption of Twitter, at 83.3% and 87.9% (untabulated), respectively. Likewise, usage of Twitter by firms does increase over time, starting at 57.4% of firms in 2011 and peaking at 78.1% of firms in 2018. Overall, our sample contains 1,560 firms that had a Twitter account.

Figure 2 Panel C presents the distribution of different tweet topics over the sample period. We find that executives have a higher proportion of tweets relating to business matters than firms, including both financial and non-financial business tweets, and that this difference is consistent throughout the sample period. In the final year of our sample, the distribution of executives' tweets is 1.0% financial, 81.6% non-financial business, and 17.5% other.

4.2.2 Determinants: Executive adoption of Twitter

Table 1 presents the univariate statistics of independent variables used for our determinants of joining Twitter model. The table splits out executive-firm-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 not on Twitter while male executives are 1.7% less likely on Twitter. Lastly, as expected, we find that extraverted CEOs are more likely to be on Twitter.

Regarding the indicator for if 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, including smaller firms and those with higher market to book ratios. Furthermore, the firms whose executives are on Twitter tend to be smaller, 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 follower accounts, 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, by if the executive or firm is on Twitter. When the firm is not on Twitter, its executive is on Twitter only 5.4% of the time, whereas if the firm is on Twitter the conditional probability that the executive is on Twitter is 7.8%.

Panels C and D present the top ten Twitter accounts by the number of posts for executives and firms, respectively. Of the top ten executive accounts, nine of the accounts are by CEOs and only one is by a CFO. Interestingly, these executives are largely from firms not represented in the list of firms with the most tweets (Panel D) – only T-Mobile is represented in both lists.

Table 2 presents three different versions of the determinants model. Column 1 presents a model only including the 2013 SEC report indicator, financial controls, and fixed effects (industry and year). As expected, we observe a positive and significant impact of the 2013 SEC report, suggesting that the report did lead to an overall increase in executives joining Twitter. We also observe a statistically significant 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.[24]

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. Second, we observe an impact of executive personality: more extraverted executives are more likely to be on Twitter, consistent with more extraverted individuals being more interested in seeking out attention.[25]

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 hears about or sees Twitter as a relevant channel before they join. 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 executive fixed effects reveals that executives in the information technology industry (*t=7.78)* and the communications industry (*t=11.31*) 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 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.

[24] 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.

[25] 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 significantly negatively related to executives joining Twitter, while agreeableness and openness are significantly positively related to executives joining Twitter.

4.2.3 Importance of Twitter as an information dissemination channel for executives

Univariate statistics for our daily sample restricted to executives on Twitter are presented in Table 3. This sample consists of 509,756 executive-firm-days, with executives posting an average of 0.45 tweets per day and their firms posting around 11.6 tweets per day. We note that the relatively low number of tweets per executive per day is in part due to the presence of 193 executives who had Twitter accounts but never tweeted during the sample.[26] We keep these executives for our tests as these executives *could*, at any time, release a public tweet; all our results are robust to dropping these executives, however, as discussed in Section 5. Among those executives on Twitter, around 67% of days in the sample are by CEOs and 34% are by CFOs,[27] and for approximately 76% of the sample the executives' firms are also on Twitter. In terms of what executives tweet about, the most common category is non-financial business, followed by other. Firms follow a similar pattern where non-financial business tweets are still the most common, followed by other tweets. While the overall rate of financial tweeting per executive-day is low, we note that financial tweets make up an overall larger portion of executives' tweets as compared to firms. Over the full sample, 0.80% of all executive tweets are financial, while only 0.34% of firm tweets are financial.

To explore if executives view Twitter as an important channel for information dissemination, we present results following regression equation (2) in Table 4. In Panel A, we examine the impact of earnings announcements and earnings conference calls on executive tweets.[28] We observe a large increase in the number of financial tweets posted around these events, and that 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.

[26] The 193 executives without tweets reported here is larger than the 160 executives without tweets mentioned for our full data collection. This is due to 33 executives having their first tweet after a point in which they drop out of our final sample due to missing controls or changing jobs to a company not included in our sample.
[27] The total percent of observations flagged as a CEO and a CFO is slightly higher than 100% due to 15 execid-gvkey pairs where an executive was serving both roles simultaneously. For such days, the executive is not double counted in our analyses.
[28] We collapse earnings announcements and earnings conference calls into one measure as these occur on the same trading day over 80% of the time in our sample. Our results are consistent and robust when separately examining the impact of earnings announcements or earnings conference calls.

For tweets about non-financial and 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 only during the trading hours of the day of announcement. Overall, the majority of the increase in tweeting by executives is in terms of financial tweets, providing support for Twitter being an important channel for disclosure in the eyes of executives.

Panel B of Table 4 presents results for 10-K and 10-Q filings. Consistent with our expectations, 10-K and 10-Q filings lead to an increase in executives posting financial information on Twitter. We observe no increase in other types of tweeting. This increase again occurs across all three examined windows: prior to trading, during trading hours on the day of release, and after trading hours. Panel C of Table 4 presents results for 8-K filings, the results are substantively similar to those for the 10-K and 10-Q filings.[29] Taking the results of all three panels together, we see strong support for executives using Twitter as a dissemination channel.

To further explore how executives post around earnings events, we present intraday distributions of tweet counts with respect to earnings announcements and earnings conference calls in Figure 3.[30] The top panels of Figure 3 show results for earnings announcements. Here, we see that both firms and executives increase their posting of financial information immediately after the announcement, with the bulk of their tweets coming between the earnings announcement and the open of the next trading day. However, while executives post around four times more financial tweets than usual during that time period, firms post around 15 times more financial tweets than usual. The bottom half of Figure 3 presents results for earnings conference calls. Here, we see that there is an uptick in financial tweet posting both right before and right after the conference call. In contrast to our results for earnings announcements, executives post comparatively extra compared to firms around earnings conference calls. Overall, we find that executives

[29] As the length of tweets allowed on Twitter was revised from 140 characters to 280 characters, it is possible that executive tweeting behavior may have been altered by this change. In an untabulated analysis, we replicate Table 4 using only the part of our sample before or after the change in tweet length. Our results are robust on both subsets.
[30] We present results only for earnings events that occur outside of trading hours, as the majority of such events occur outside trading hours. We do not present results for 10-K, 10-Q, or 8-K filings as our database lacks precise timestamps for these filings.

appear to focus more on posting around earnings conference calls, while firms focus more on posting around earnings announcements.

Overall, the findings in Table 4 and Figure 3 present strong results in favor of executives viewing Twitter as an important dissemination channel.[31] We find evidence that executives' tweeting behavior responds to a wide variety of information events.

4.2.4 Market reaction to executives' tweets (H1)

Given the results on the importance of Twitter as an information dissemination channel, it appears credible that executive tweets could contain useful information for investors. To test Hypothesis 1, we run regression equation (3) and present the results in Table 5. The first column presents results restricted to tweets that occur during trading hours. Such tweets can be highly impactful as investors can act immediately on anything that is posted. For tweets posted by executives, we find that financial tweets drive a statistically significant increase in absolute market model return, while other tweet types do not impact stock return. Executive's financial tweets lead to an increase in absolute market model return of 0.3% per tweet. We also find a statistically significant increase in absolute market model return to firm financial tweets at 0.1% per tweet. The reaction to executive financial tweets during trading is significantly larger when testing the difference in coefficients with an F-test ($p = 0.024$), indicating that executive tweets are not only important during trading, but perhaps actually more important than firm tweets when they occur. All other tweet types either have no effect or lead to a decrease.

Column 2 of Table 5 shows results examining the impact of tweets that were posted before trading, i.e., from the close of the prior trading day to the open of the current trading day. Examining these tweets mitigates the potential endogeneity concern that tweets released during the trading day could be a reaction to a large stock price movement during that day.[32] Since the tweets examined in column 2 all were posted

---

[31] We caveat that our tests can only speak to the perspective of those executives who maintained publicly identifiable accounts on Twitter. Executives who either maintain a private or anonymous account (or no account at all) may not view Twitter as an important dissemination channel. However, executives with publicly identifiable Twitter accounts make up a non-trivial subset of all executives by the end of our sample in 2018.

[32] This endogeneity concern could also potentially be addressed by looking at intraday trading windows around tweets released during trading. In untabulated tests using TAQ data for intraday returns, we do not find any significant

prior to the open of the stock market for the day, the tweets are front running any possible changes in stock prices. In this specification, we continue to see a strong impact of financial tweets by executives, at a 0.2% increase in absolute market model return per financial tweet. For firms we also continue to see a significant increase in absolute market model return, at 0.2% per tweet.

Column 3 presents a combined model. Here we document that the impact of financial tweets during and before trading are both significant – one does not swamp out the other. Using this specification, we can estimate the overall impact of executives' financial tweets as a portion of the reaction to all financial tweets. Despite executives' financial tweets comprising only 8.3% of all financial tweets in the sample, the aggregate impact of executives' financial tweets is 14.2% of the total impact.

Column 4 presents the same analysis as column three but includes an additional control for major firm events (earnings announcements, earnings conference calls, and 10-K, 10-Q, and 8-K filings). In this analysis, we see that the reaction to executive financial tweets is not subsumed by the event control, and that the magnitude of the effect of executive financial tweets remains similar. We do note that the coefficient on firm financial tweets during trading drops out, however.

Column 5 presents a more refined sample in which observations are included only if the executive and firm both have Twitter accounts as of the trading day. This controls for potential concerns that the sample in the other panels may be mismatched or bias against firms, as our primary sample requires executives, but not firms, to all be on Twitter. We continue to find that executives' tweets in both periods drive a stock market reaction in this sample. We also continue to find that executive tweets posted during trading drive a statistically significantly larger reaction than firm tweets posted during trading. In terms of economic significance, executives' financial tweets in this sample comprise a slightly higher percentage of the overall impact of financial tweets, contributing 14.7% of the total reaction to financial tweets.

---

reaction in windows up to 1 hour long. The seeming slower reaction implied by our results is consistent with Twitter acting more as a source of information for retail investors than for institutional investors. Further consistent with this notion, if we replicate Table 5 column 1 using $|MMR_{t+1}|$ as the dependent variable (untabulated), we continue to document a positive and statistically significant (though weaker) coefficient on executive financial tweets, suggesting the time it takes investors to fully react to the information is longer than just a short intraday window.

To ensure that the stock reaction we observe is not due only to executives reacting *ex post* to financial events, we construct a subsample test focused on days with earnings events (earnings announcements and conference calls). For these events, we have precise information on when the event occurred (to the second), and as such we are able to separate out tweets based on whether they occurred before or after the earnings event. For days that have both an earnings conference call and an earnings announcement, we take the earlier of the two as our earnings event time. In Table 6, we present our results. Column 1 examines earnings events that occur during trading hours. For these events, we find that the only tweets driving stock market reaction are financial tweets by executives that occurred before the trading period began. As such, these tweets all occurred prior to the earnings event, highlighting that the tweets are not a reaction to the stock market's reaction to the earnings event. We find no positive effect for firm tweets, though we do document a negative impact of firm financial tweets during trading on absolute market model return. In column 2 we examine the sample of events where the announcement occurred before trading hours. In such cases, we do see that the reaction in the stock market comes from executive's financial tweets that occurred during trading hours, and consequently that occurred after the earnings event. Such tweets could include reaction to stock market movement, further dissemination of the earnings information, or interpretation of the earnings event. Taken together, we see that at least a portion of the market reaction to executive tweets cannot be driven by the reaction of the executive to the stock market reaction to the financial event.

4.2.5 Market response mechanism (H2)

Table 7 presents the results for our test of Hypothesis 2 following regression equation (4). For this regression, we require that both the executive and firm are on Twitter, as the similarity measure that is central to the mechanism test requires both parties to be able to tweet for the measure to be defined.[33] We present results both without any control for firm events (first two columns) and with a control for firm events (last two columns). The first column presents results for tweets that were posted during trading hours,

[33] Our results are robust to using the same base sample as in Table 5, where we set *Tweet similarity* to 0 whenever an executive's firm is not on Twitter.

while the second column presents results for tweets that were posted prior to trading. First, we aim to distinguish between the new information (Hypothesis 2a) and trust (Hypothesis 2b) mechanisms. For tweets both before and during trading we observe the same impacts: the coefficient on the interaction between *Financial tweets, Executive* and *Tweet similarity* is positive and significant.[34] This supports the trust mechanism stated in Hypothesis 2b, that investors react more strongly when executives post financial information which is more similar to the information previously posted by their firm. As such, the tweets that the stock market is reacting to are less likely to contain new information, but instead provide second-order information as to the reliability of past statements made by the firm on Twitter.

To examine a stronger case for the information content mechanism, we also include an interaction between *Financial tweets, Executive* and *No firm tweets*. This interaction tests *Hypothesis 2c* by capturing the impact of an executive's financial tweets when the executive's firm has not been posting on Twitter in a 48-hour period leading up to the executive's financial tweet. In such cases, there is no past dissemination on Twitter for investors to rely on, and thus what an executive says is likely to be new information content (within the channel of Twitter). As we observe a positive and significant coefficient in both tests, this provides some support for the information content channel.

When we shift our focus to the models with firm event controls, we see that the control subsumes the effect of executive tweets during trading (where the effect was weaker), but the effect remains for tweets posted prior to trading. For these tweets, we continue to find support for the trust mechanism, as executive tweets posted before trading that are more similar to prior firm tweets continue to drive the result. Likewise, we continue to find support for the new information mechanism when the firm has not recently tweeted.

Taken together, our results indicate that both mechanisms, trust and information content, can play a role in how investors react to executive tweets. We note that there are firm tweets in 49% of executive-day observations with executive financial tweets, and thus both effects are economically meaningful. When

[34] Our results are robust to an alternative specification of our similarity measure using Manhattan distance (L1 norm) as the distance measure underlying our similarity computations. Using this alternative metric, all results are inferentially identical. Our results are also robust to using different windows of time to compare tweets across for the similarity measure, including 1 and 7 days.

a firm is active on Twitter, its executive can serve a confirmatory role, providing investors with additional trust on the information that the firm has already disclosed. When a firm is not active on Twitter, then the executive can fill the void left by the firm and take on an information-providing role.

5 Additional tests

To further examine where the trust and new information mechanisms are most effective, we conduct three partitioned sample tests on the results for Hypothesis 2 based on three characteristics: firm size, institutional ownership, and executives' follower count. For firm size and institutional ownership, we partition the sample on the median of the set of firms with executives on Twitter. For executives' follower count, we split on whether the executive has as many followers as the firm or not. We present the results in Table 8. All panels follow the same equation, controls, and fixed effects as columns 3 and 4 of Table 7. Panel A shows the results for tweets before trading hours. Examining the interaction terms of the regressions, we find that reaction to executive financial tweets is significantly only for those executives from larger firms or firms with higher institutional ownership. This reaction is conditional on either the tweets being similar to past firm tweets (trust mechanism) or the firm having not tweeted over the prior two days (information content). We do not find any significant results when partitioning on executive follower count in this time period.

In Panel B of Table 8 we present results for tweets during trading hours. Here, based on the interaction terms, we see that the executives that receive the most attention from the market are different from the before trading analysis. During trading, it is the executives at smaller firms and firms with less institutional ownership that are driving stock market reaction, along with executives with lower following as compared to their firms. As such, generally the firms with less efficient information environments are the source of the impact of executive financial tweets during trading. Again, we find support for both the trust mechanism and information content. For executives with higher following, we find support for the trust mechanism on both sides of the split, while we find support for information content only for executives with less following than their firms.

As the reason for executives to not tweet is unobservable, we cannot say for sure why some executives in our sample never tweeted. While our main results include these executives under the assumption that these executives could have tweeted at any point in time if they chose to, it is possible there were external factors preventing them from tweeting. As such, we re-run our primary results removing any executives who have, as of a given date, never tweeted. As such, our sample becomes executives who have tweeted by day *t*. We also examine other cutoffs of 10 tweets and 100 tweets by day *t*. For each cutoff (1, 10, or 100 tweets), we find generally consistent results for the determinants model. The primary differences are that female executives are less likely to have posted any tweet despite being more likely to have an account, and the SEC report is no longer significant. We continue to find that executives view Twitter as an important information dissemination channel by tweeting financial information around major firm events. Furthermore, we find that the stock market reaction is consistent across all three samples, with investors reacting to executive financial tweets posted both during trading as well as before trading. Lastly, our mechanism test holds on all three samples, showing both that trust leads the market to respond to executive tweets that are similar to their firms' tweets, and that executives can fill an information role in the absence of firm tweets. Overall, our results are robust to requiring executives to have tweeted at least once, ten, or one hundred times.

6 Conclusion

This paper examines the tweeting behavior of executives. We find that there has been a large increase in the number of executives on Twitter from 3% in 2011 to 12% in 2018, and that the executives most likely to be on Twitter are younger, female, more extraverted, and working for growth-oriented or riskier firms. We then document that executives tweet about financial information around important financial and non-financial business events, indicating that executives view Twitter as a useful channel for information dissemination. We find that the market reacts to financial tweets by executives and that this reaction is much stronger than the market's reaction to financial tweets by firms. Lastly, we examine the mechanism underlying the market reaction using an innovative measure based on the similarity of content between executives' and firms' tweets. We find that the market reacts more to executives' financial tweets that contain content similar to firms' prior tweets, supporting the trust mechanism that has been documented in the experimental literature (Elliott et al. 2018). We also document a role for executives to play in relaying new information on Twitter, as, in the absence of any recent tweets from their firms, executives' tweets also lead to market reaction. While this paper examines the extent of market reaction to executive tweets and the mechanism that drives it, we do not rigorously examine the reasons why executives tweet. Future research is needed to understand whether and how executives strategically use social media to move markets or impact stakeholders' views of the firm. Furthermore, future research is needed to understand executives' incentives or motivation for using social media for professional purposes.

References

Arya S, Mount DM (1993) Approximate Nearest Neighbor Queries in Fixed Dimensions. *Proc. 4th Annu. ACM/SIGACT-SIAM Symp. Discrete Algorithms*, 271–280.

Bartov E, Faurel, L, Mohanram PS (2018) Can Twitter Help Predict Firm-Level Earnings and Stock Returns? *Accounting Rev.* 93 (3): 25–57.

Blankespoor E, Miller GS, White HD (2014) The Role of Dissemination in Market Liquidity: Evidence from Firms' Use of Twitter™. *Accounting Rev.* 89 (1): 79–112.

Blankespoor E, deHaan E, Marinovic I (2020) Disclosure Processing Costs, Investors' Information Choice, and Equity Market Outcomes: A Review. *J. Accounting Econom.* 70 (2-3): 101344.

Blei DM, Ng AY, Jordan MI (2003) Latent Dirichlet Allocation. *J. Mach. Learn. Res.* 3 (March): 993–1022.

Bollen J, Mao H, Zeng X (2011) Twitter Mood Predicts the Stock Market. *J. Comput. Sci.* 2 (1): 1–8.

Brandfog (2012) CEO, Social Media & Leadership Survey. Brandfog, New York.

Brown NC, Crowley RM, Elliott WB (2020) What Are You Saying? Using Topic to Detect Financial Misreporting. *J. Accounting Res.* 58 (1): 237–291.

Call AC, Martin GS, Sharp NY, Wilde JH (2018) Whistleblowers and outcomes of financial misrepresentation enforcement actions. *J. Accounting Res.* 56 (1): 123–171.

Campbell J, Chen H, Dhaliwal DS, Lu H, Steele L (2014) The information content of mandatory risk factor disclosures in corporate filings. *Rev. Accounting Stud.* 19 (1): 396-455.

Cer D, Yang Y, Kong SY, Hua N, Limtiaco N, John RS, Constant N, Guajardo-Cespedes M, Yuan S, Tar C, Sung YH, Strope B, and Kurzweil R (2018) Universal Sentence Encoder. ArXiv preprint. Available at: http://arxiv.org/abs/1803.11175.

Chen H, Hwang BH, Liu B (2022) The Adoption of Social Technologies and the Consequences for Financial Markets. Working paper, Nanyang Technological University, Singapore.

Colgan J, Chow L (2011) How Twitter Was Nearly Called Twitch: Twitter Co-Founder Jack Dorsey on Coming Up with a Name. *WNYC* (July 18), https://www.wnyc.org/story/146115-twitter-co-founder-jack-dorsey-how-his-company-was-nearly-called-twitch/.

Correia S (2016) A Feasible Estimator for Linear Models with Multi-Way Fixed Effects. Working paper, Duke University, Durham.

Correia S, Guimarães P, Zylkin T (2019) Ppmlhdfe: Fast Poisson Estimation with High-Dimensional Fixed Effects. ArXiv preprint. Available at: http://arxiv.org/abs/1903.01690.

Crowley RM, Huang W, Lu H (2022) Discretionary Dissemination on Twitter. Working paper, Rotman School of Management, Singapore Management University School of Accountancy.

Curtis A, Richardson VJ, Schmardebeck R (2016) Investor Attention and the Pricing of Earnings News. *Handbook of Sentiment Analysis in Finance* (Chapter 8), 212-232.

Dyer T, Lang M, Stice-Lawrence L (2017) The Evolution of 10-K Textual Disclosure: Evidence from Latent Dirichlet Allocation. *J. Accounting Econom.* 64 (2): 221–45.

Elliott WB, Grant S, Hodge F (2018) Negative News and Investor Trust: The Role of $ Firm and #CEO Twitter Use. *J. Accounting Res.* 56 (5): 1483–1519.

Gourieroux C, Monfort A, Trognon A (1984) Pseudo maximum likelihood methods: Applications to Poisson models. *Econometrica*. 701–720.

Grant S, Hodge F, Sinha R (2018) How Disclosure Medium Affects Investor Reactions to CEO Bragging, Modesty, and Humblebragging. *Account. Organ. Soc.* 68-69: 118–134.

Green TC, Jame R, Lock B (2019) Executive Extraversion: Career and Firm Outcomes. *Accounting Rev.* 94 (3): 177–204.

Hope OK, Hu D, Lu H (2016) The Benefits of Specific Risk-Factor Disclosures. *Rev. Accounting Stud.* 21 (4): 1005–1045.

Huang AH, Lehavy R, Zang AY, Zheng R (2018) Analyst Information Discovery and Interpretation Roles: A Topic Modeling Approach. *Management Sci.* 64 (6): 2833–2855.

Java A, Song X, Finin T, Tseng B (2007) Why We Twitter: Understanding Microblogging Usage and Communities. *Proc. 9th WebKDD and 1st SNA-KDD 2007 Workshop on Web Mining and Social Network Analysis*, 56–65.

Jung MJ, Naughton JP, Tahoun A, Wang C (2018) Do Firms Strategically Disseminate? Evidence from Corporate Use of Social Media. *Accounting Rev.* 93 (4): 225–252.

Kim I, Skinner DJ (2012) Measuring securities litigation risk. *J. Accounting Econom.* 53 (1-2): 290–310.

Kwoh L, Korn M (2012) 140 Characters of Risk: Some CEOs Fear Twitter. *Wall Street Journal* (September 26), https://www.wsj.com/articles/SB10000872396390444083304578018423363962886.

Lee LF, Hutton AP, Shu S (2015) The Role of Social Media in the Capital Market: Evidence from Consumer Product Recalls. *J. Accounting Res.* 53 (2): 367–404.

Lewicki RJ, Bunker BB (1996) Developing and Maintaining Trust in Work Relationships. Kramer RM, Tyler TR, eds. *Trust in Organizations: Frontiers of Theory and Research* (Sage, Thousand Oaks, CA), 114–39.

Lewis DD, Yang Y, Russell-Rose T, Li F (2004) Rcv1: A new benchmark collection for text categorization research. *J. Mach. Learn. Res.* 5 (Apr): 361–397.

Lin KY, Lu HP (2011) Why People Use Social Networking Sites: An Empirical Study Integrating Network Externalities and Motivation Theory. *Comput. Hum. Behav.* 27 (3): 1152–1161.

Mao Y, Wei W, Wang B, Liu B (2012) Correlating S&P 500 Stocks with Twitter Data. *Proc. 1st ACM International Workshop on Hot Topics on Interdisciplinary Social Networks Research*, 69–72.

Mairesse F, Walker MA, Mehl MR, Moore RK (2007) Using linguistic cues for the automatic recognition of personality in conversation and text. *J. Artif. Intell. Res.* 30: 457–500.

Mikolov T, Chen K, Corrado G, Dean J (2013) Efficient Estimation of Word Representations in Vector Space. ArXiv preprint. Available at: http://arxiv.org/abs/1301.3781.

Nekrasov A, Teoh S, Wu S (2021) Visuals and Attention to Earnings News on Twitter. *Rev. Accounting Stud.* Forthcoming.

Pennington J, Socher R, Manning C (2014) Glove: Global Vectors for Word Representation. *Proc. 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, 1532–1543.

Pew Research Center (2015) Men catch up with women on overall social media use. Pew Research Center, Washington, DC.

Pew Research Center (2018) Social Media Use 2018: Demographics and Statistics. Pew Research Center, Washington, DC.

Sprenger TO, Tumasjan A, Sandner PG, Welpe IM (2014) Tweets and Trades: The Information Content of Stock Microblogs. *Eur. Financial Manag.* 20 (5): 926–957.

Toubia O, Stephen AT (2013) Intrinsic vs. Image-Related Utility in Social Media: Why Do People Contribute Content to Twitter? *Marketing Sci*.32 (3): 368–92.

U.S. Securities and Exchange Commission (2008) Commission Guidance on the Use of Company Web Sites. Release Nos. 34-58288, IC-28351. U.S. Securities and Exchange Commission, Washington, DC.

U.S. Securities and Exchange Commission (2013) Report of Investigation Pursuant to Section 21(a) of the Securities Exchange Act of 1934: Netflix, Inc., and Reed Hastings. Release No. 69279. U.S. Securities and Exchange Commission, Washington, DC.

Weber Shandwick (2014) The Social CEO: Executives Tell All. Weber Shandwick, New York.

Zhao WX, Jiang J, Weng J, He J, Lim EP, Yan H, Li X (2011) Comparing Twitter and Traditional Media Using Topic Models. Clough P, Foley C, Gurrin C, Lee H, Jones G, Kraaij W, Mudoch V eds. *Advances in Information Retrieval* (Springer, Berlin, Heidelberg), 338–349.

Appendix A. Variable Definitions

Variable	**Definition**
Tweet count variables	
Financial tweets, Executive or Financial tweets, Firm	The number of financial tweets posted by the executive (or firm) during a given window as classified by the Twitter-LDA model described in Section 3.2.1. [Twitter API & Gnip]
Non-fin business tweets, Executive or Non-fin business tweets, Firm	The number of tweets about business-oriented topics other than financial topics posted by the executive (or firm) during a given window as classified by the Twitter-LDA model described in Section 3.2.1. [Twitter API & Gnip]
Other tweets, Executive or Other tweets, Firm	The number of tweets posted by the executive (or firm) during a given window not included in the related *Financial tweets* and *Non-fin business tweets* measures as classified by the Twitter-LDA model described in Section 3.2.1. [Twitter API & Gnip]
Total Tweets, Firm	The total number of tweets posted by the firm from joining Twitter up to the start of a given window.
Dependent variables	
Joined Twitter, Executive	An indicator for if the executive has opened a Twitter account by the given date [Twitter API]
$MMRet_t$	Market model return on day *t*, calculated using a daily frequency, using a daily updated beta with respect to the S&P 500 index calculated over the prior quarter (63 trading days) [CRSP]
Independent variables	
10-K or 10-Q filings	An indicator for if a 10-K or 10-Q filing was released on the given trading day, based on *FINDEXDATE* from WRDS SEC Analytics
8-K filings	The number of 8-K filings released on a given trading day, based on *FINDEXDATE* from WRDS SEC Analytics
Earnings events	An indicator for if the firm released an earnings announcement (annual or quarterly) on the given trading day or conducted an earnings conference call during the given window [I/B/E/S & Capital IQ]
No firm tweets	An indicator variable equal to 1 when *Tweet Similarity* is undefined due to there being 0 firm tweets to match to the executive's financial tweet in the 48 hours preceding the executive's financial tweet.
Similarity undefined	An indicator variable equal to 1 when *Tweet Similarity* is undefined due to either there being no financial tweet posted by the executive in the specified window or no firm tweet to match to a posted executive tweet.

Tweet similarity	The similarity of financial tweets by an executive to the most similar tweet by the executive's firm in the 48 hours preceding the executive's financial tweet. Similarity is calculated as (1 – Distance / 2) and is thus scaled to the range of [0,1], where 1 is most similar. Distance is measured as the minimum Euclidean distance (L2 norm) between the USE vector representing the executive's financial tweet and the USE vectors representing the tweets by the executive's firm. USE vectors are calculated as described in Appendix E. [Twitter API & Gnip]
Control variables (determinants model)	
CEO	Indicator, "1" if the executive is the CEO [Execucomp]
CFO	Indicator, "1" if the executive is the CFO [Execucomp)
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]
Female	Indicator, "1" if the executive is female [Execucomp]
SEC Regulation	1 if the date is at or later than April 2, 2013, else 0
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%
Firm event	An indicator equal to one on trading days where the firm has an earnings event (earnings announcement or conference call) or an SEC filing release (forms 10-K, 10-Q, or 8-K), else 0.
Litigation Risk	Litigation risk measured following Kim and Skinner (2012), updated yearly, and scaled linearly such that the lowest risk firm measures 0 and the highest risk firm measures 1 [Compustat & CRSP]
MTB	Market to book value, calculated as market value (mkvaltq) divided by total assets (atq), Winsorized at 5% and 95%
ROA	Return on assets, calculated as Net income (niq) divided by total assets (atq), Winsorized at 5% and 95%
Size	Log of assets (atq), Winsorized at 5% and 95%

Control variables (Twitter)	Note: Excluding *Firm on Twitter* and the *Total tweets* measures, these control variables are backfilled from the time of collection as historic data is unavailable from our data sources. Firm and CEO data is first available as of January 2017 and CFO data is first available as of June 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.
1+ tweets, Firm	An indicator for if the firm associated with the given executive has joined Twitter and has posted at least 1 tweet cumulatively by the end of the given day
10+ tweets, Firm	An indicator for if the firm associated with the given executive has joined Twitter and has posted at least 10 tweets cumulatively by the end of the given day
100+ tweets, Firm	An indicator for if the firm associated with the given executive has joined Twitter and has posted at least 100 tweets cumulatively by the end of the given day
Days since firm joined	If the firm has joined Twitter, then this measure equals the number of days since the firm joined Twitter, else 0
Joined Twitter, Firm	An indicator for if the firm associated with the executive has joined Twitter
$log(Followers_{Exec})$	The log of one plus the number of Twitter accounts following the executive (CEO or CFO) on Twitter [Twitter API]
$log(Followers_{Firm})$	The log of one plus the number of Twitter accounts following the firm on Twitter [Twitter API]
$log(Following_{Exec})$	The log of one plus the number of Twitter accounts the executive (CEO or CFO) follows on Twitter [Twitter API]
$log(Following_{Firm})$	The log of one plus the number of Twitter accounts the firm follows on Twitter [Twitter API]
$log(Total\ tweets_{Exec})$	The log of one plus the number of tweets that the executive (CEO or CFO) has posted up to the given date [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]
Partitioning variables	
Size	Log of assets (atq), Winsorized at 5% and 95%
Institutional ownership	Percent of ownership held by institutional ownership [Thomson Reuters 13F]
Exec vs firm followers	An indicator variable equal to 1 if the number of followers the executive has ($Followers_{Exec}$) is greater than or equal to the number of followers the executive's firm has ($Followers_{Firm}$) [Twitter API]

Appendix B. Tweet examples by category

Financial

Omar Ishrak, @MedtronicCEO, CEO of Medtronic, 2013.02.19, Tweet ID 304003694133915650

> Continuing to execute in both our product & SG&A cost reduction initiatives will provide consistent EPS leverage #MDTEarnings

Mike Jackson, @CEOMikeJackson, CEO of AutoNation, 2012.04.03, Tweet ID 187147614582611968

> With ample credit, great products & strong Toyota & Honda inventory'we raised our '12 sales forecast to mid 14 million vehicles

Marcelo Claure, @marceloclaure, CEO of Sprint, 2016.05.03, Tweet ID 727473544712585219

> 1/ FY2015 was a transformational year. Positive operating income for the first time in 9 years! https://t.co/hxEkNDlpWO

Non-financial business

Mark T. Bertolini, @mtbert, CEO of Aetna, 2012.27.02, Tweet ID 174165135634608129

> 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)

Jim Whitehurst, @Jwhitehurst, CEO of Redhat, 2016.08.16, Tweet ID 765675513092378624

> Great time chatting with our Customer Platform team. Keep up the great work!! #LifeAtRedHat https://t.co/Otfvfqhmfa

Carl Bass, @carlbass, CEO of Autodesk, 2014.04.04, Tweet ID 451894164620578817

> Giving keynote tomorrow at #inside3Dprinting Talking about the good, bad of #3Dprinting and the future of software

Other

Bob Carrigan, @BobCarrigan, CEO of Dun & Bradstreet, 2010.05.12, Tweet 13892580082

> 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!

Carl Bass, @carlbass, CEO of Autodesk, 2014.04.10, Tweet ID 454302765246726144

> Another great day of spring skiing in the Alps http://t.co/DhySN4hSud

Tony Thomas, @TonyThomasWIN, CEO of Windstream, 2015.04.19, Tweet ID 589958494951964672

Hail #uncool Mother Nature showing her fury http://t.co/HwqQa6tK57

Appendix C. Discussion of the Twitter-LDA model

The Twitter-LDA model used by this paper is the same model as used by Crowley et al. (2022). That model finds 60 topics throughout a large set of financial tweets. The model then constructs a set of weighted dictionaries that represent each topic, allowing us to classify tweets into an individual topic. The following table presents the words with the highest weighting from each topic group. To provide more insight on the non-financial business topics, we present the top words based on four sub-categorizations: marketing, support, conference, and other business.

Categorization	Top 10 words	10 Most frequent words used by executives in topic	5 most frequent bigrams used by executives in topic
Financial (1)	market, growth, markets, trading, earnings, global, report, quarter, results, energy	market, growth, results, markets, earnings, quarter, innovation, economic, year, rate	Bull market, earnings call, economic growth, long term, revenue growth
Non-Financial Business (42)			
Marketing (24)	pass, free, enjoy, shipping, heres, life, love, time, #apple, shop	time, today, innovation, tech, day, love, make, people, business, great	Tech innovation, mobile innovation, science bigdata, tech science, innovation awesome
Support (5)	dm, store, customer, team, flight, send, number, hear, feedback, claim	team, customer, network, service, change, innovation, share, story, experience, care	Customer service, customer experience, leadership team, team members, tech innovation
Conference (5)	booth, join, today, #iot, learn, great, live, week, register, stop	innovation, tech, ai, technology, iot, ceo, business, bigdata, week, video	tech innovation, innovation tech, ai machine learning, technology innovation, ml dl
Other Business (8)	#jobs, dm, email, #job, hear, send, contact, hiring, working, details	Innovation, work, email, customers, support, working, proud, tech, future, world	Tech innovation, innovation tech, email details, health care, email ceo
Other (17)	stay, travelers, dont, rating, order, joe, tweet, collection, enjoy, book	great, good, innovation, awesome, follow, amazing, happy, tech, watch, hear	happy birthday, great day, tech innovation, pls email, stay tuned

Note: The first column presents the name of the category or subcategory following Crowley et al. (2022), 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 10 words based on the weights reported by LDA. The third and fourth columns present information on the most common words and bigrams used in tweets by executives within each category or subcategory. For these columns, we remove all stopwords using the SMART stopword list (as in Lewis et al. 2004), proper nouns, URLs, punctuation, and Twitter-specific grammar such as "RT" (marking a message as retweeting or quoting text). We present the 10 most frequent words and 5 most frequent bigrams from the tweets underlying our sample from 2011-2018.

Appendix D. Twitter-LDA validation

To validate the Twitter-LDA algorithm (Zhao et al. 2011) that we implemented for determining tweets' content, we randomly select 500 executive tweets from each predicted category: financial, non-financial business, and other. For each category we read through the 500 tweets and manually classify them based on the textual content of the tweet. In the table below, we present the results of this validation as a confusion matrix, as well as the 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 measure has the highest sensitivity of any class, indicating a low prevalence of Type I 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 in fact financial in nature. Furthermore, our financial tweet measure likewise has the highest specificity at 87.5%, indicating a low prevalence of Type II 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 Twitter-LDA as performing well as a classifier for our use-case.

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

	Twitter-LDA classification		
Manual classification	**Financial**	**Non-financial business**	**Other**
Financial	**71.4%**	0.4%	0.2%
	357	2	1
Non-financial business	15.8%	**66.2%**	26.6%
	79	**331**	133
Other	12.8%	33.4%	**73.2%**
	64	167	**366**
Sensitivity	99.2%	61.0%	61.3%
Specificity	87.5%	82.3%	85.2%

Appendix E. 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 vectors space. Other examples of embeddings include word embedding algorithms like word2vec (Mikolov et al. 2013) and GloVe (Pennington et al. 2014), which are both 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.[35]

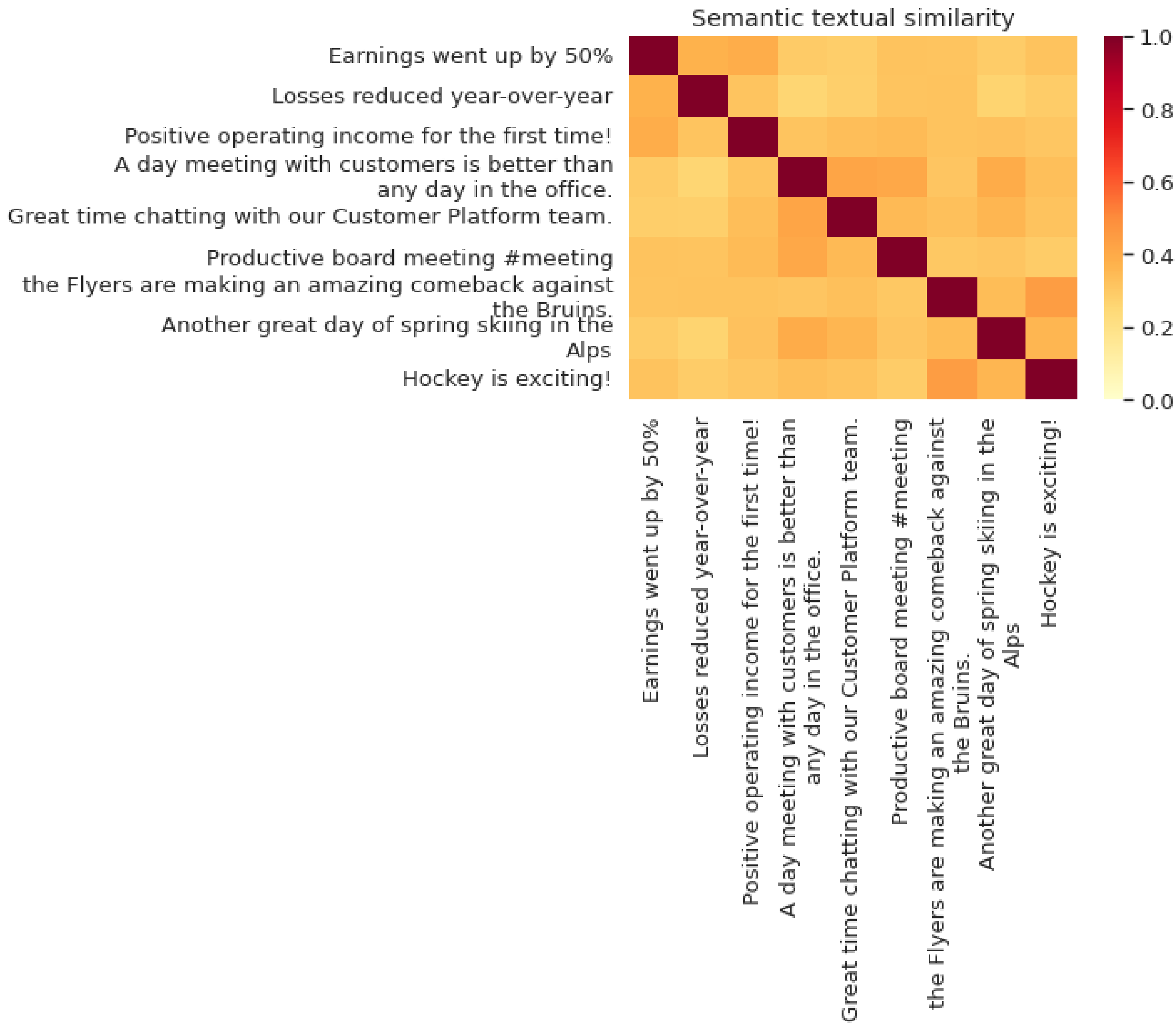
The USE methodology converts each tweet in our data into 512-dimensional unit vectors that map somewhere into a 512-dimensional vector space. Within this space, the closer two vectors are, the more similar is the meaning of the tweets the vectors represent. To calculate the distance between vectors, 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 1. For L2 distance, we normalize by dividing by 2, as the farthest distance under an L2 norm for any two n-dimensional unit vectors is 2. For L1 distance, 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 the figure below, we present an example illustrating output for a set of Twitter-like 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 financially related.

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

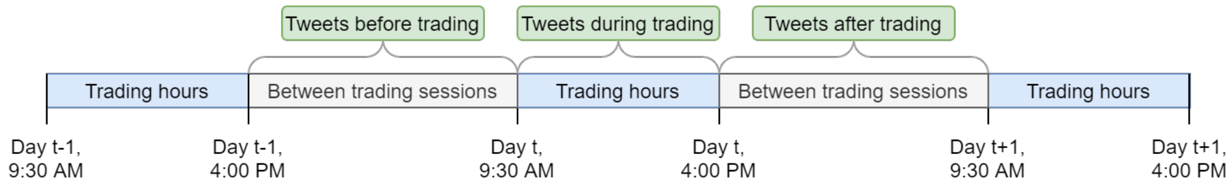
There is likewise a visual clustering in the middle 3x3 set of cells, indicating similarity within the non-financial business tweets. Lastly, two of the three other tweets show a higher degree of similarity, with one tweet explicitly talking about a hockey game and another discussing the sport more generally. 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 would assign very low similarity scores to both the discussed examples, because the word choices do not overlap.

Example Twitter-like text similarities:



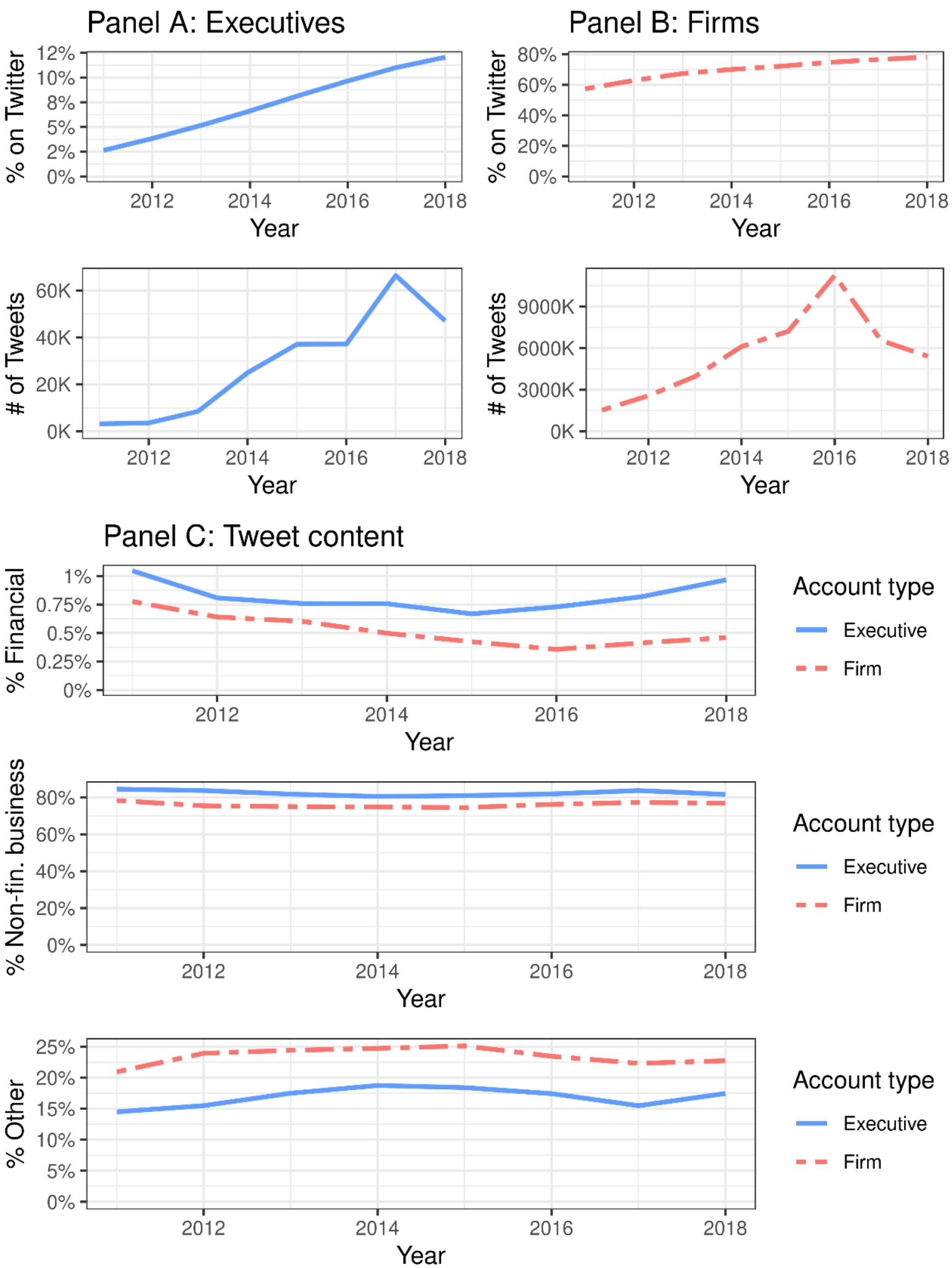
Note: This figure shows some Twitter-like text (a mix of tweets, shortened tweets, and contrived text for illustrative purposes. The first (second, third) three messages represent *financial* (*non-financial business*, *other*) content. For *financial*, note how the algorithm can pick up the similarity between "earnings," "losses" in the context of year-over-year, 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 a couple of 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.

Figure 1: Timeline illustrating tweet windows



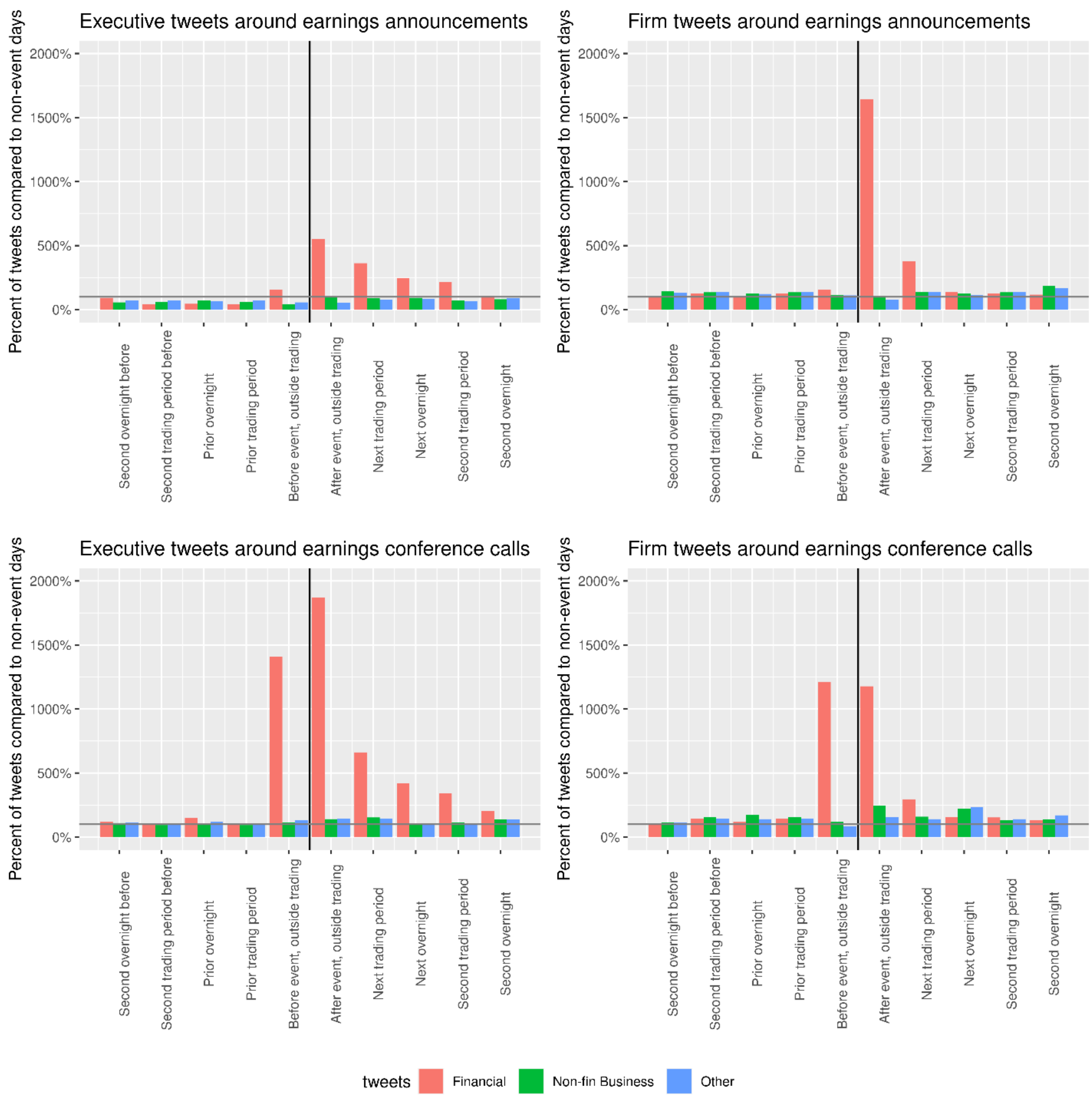
Note: This figure shows the timing of the three windows of tweets examined in this paper: 1) *before trading*, *during trading*, and *after trading*. *Before trading* occurs between the end of the day *t-1* trading session and the start of trading on day *t*. *During trading* occurs during the trading 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*.

Figure 2: Twitter accounts and tweets by year



Note: Panel A (B) presents the percent of executives (firms) and the number of tweets by executives (firms) on Twitter by year. Panel C shows the average percent of tweets categorized as *financial*, *non-financial business*, and *other* on Twitter by year from 2011 through 2018, split by firm and executive.

Figure 3: 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 ("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 1: Univariate statistics, quarterly sample of all executives, 2011 through 2018

Panel A: Univariate differences by executive Twitter account status

	Executive not on Twitter		**Executive on Twitter**		**On Twitter minus not on Twitter**	
Variables	**Mean**	**S.D.**	**Mean**	**S.D.**	**Difference**	**t-stat**
Executive age	54.4	7.34	52.2	6.95	-2.2***	-25.3
Female	0.073	0.260	0.089	0.284	0.016***	4.99
Extraversion	3.90	0.589	4.05	0.614	0.15***	18.1
SEC Regulation	0.668	0.471	0.865	0.342	0.197***	36.0
Size	8.13	1.72	7.72	1.78	-0.41***	-20.0
ROA	0.010	0.029	0.008	0.033	-0.002***	-5.12
MTB	1.35	1.37	1.66	1.70	0.31***	18.7
Debt	0.575	0.248	0.557	0.250	-0.018***	-6.40
Litigation risk	0.517	0.120	.560	0.123	0.043***	30.4
Joined Twitter, Firm	0.681	0.466	0.758	0.429	0.077***	14.1
log(Followers$_{Firm}$)	5.18	4.61	6.65	4.80	1.47***	27.1
log(Following$_{Firm}$)	3.64	3.35	4.69	3.37	1.05***	26.5
log(Total tweets$_{Firm}$)	4.08	3.78	5.45	3.93	1.37***	30.7
Observations	**101,629**		**7,718**			

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%
	(32,467)	(1,871)	(34,338)
Firm on Twitter	63.3%	5.35%	68.6%
	(69,162)	(5,847)	(75,009)
Total	92.9%	7.06%	100%
	(101,629)	(7,718)	(109,347)

Panel C: Top executive accounts on Twitter by number of tweets

#	Executive	Title	Company	Twitter handle	Twitter ID	# of tweets
1	John J. Legere	CEO	T-Mobile	JohnLegere	1394399438	42,987
2	Dror Niv	CEO	Global Brokerage	Nivo0o0	277618799	22,178
3	Marc R. Benioff	CEO	Salesforce.com	Benioff	22330739	21,389
4	Kevin E. Bryant	CFO	Great Plains Energy	Educated_Change	127991676	20,625
5	Jack Dorsey	CEO	Twitter	jack	12	17,912
6	Raul Marcelo Claure	CEO	Sprint	marceloclaure	92639420	12,501
7	Mark J. T. Thompson	CEO	New York Times	SuccessMatters	19200585	6,727
8	Bryan K. Bedford	CEO	Republic Airways	Bryan_Bedford	19673177	5,277
9	Jonathan Oringer	CEO	Shutterstock	jonoringer	23890475	5,261
10	Karl McDonnell	CEO	Strategic Education	Karl_McDonnell	249441251	4,870

Panel D: Top company accounts on Twitter by number of tweets

#	Company	Twitter handle	Twitter ID	# of tweets
1	American Airlines Group Inc	AmericanAir	22536055	2,012,342
2	Nordstrom Inc	Nordstrom	15162193	1,356,592
3	United Airlines Holdings Inc	united	260907612	1,029,583
4	Delta Air Lines Inc	Delta	5920532	860,100
5	Southwest Airlines	SouthwestAir	7212562	743,331
6	Chipotle Mexican Grill Inc	ChipotleTweets	141341662	742,697
7	McDonald's Corp	McDonalds	71026122	721,442
8	Jetblue Airways Corp	JetBlue	6449282	537,624
9	Walmart Inc	Walmart	17137891	521,642
10	T-Mobile US Inc	T-Mobile	17338082	482,825

Note: Panel A presents univariate statistics of the sample of quarter-executive-firms from 2011 through the end of 2018. The first four columns describe the means and standard deviations for the sample of quarter-executive-firm observations where the executive is or is not on Twitter. The fifth column shows the difference of characteristics between executive on Twitter and executive not on Twitter observations, while the sixth column shows the t-statistic of the difference. 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. Panel C (Panel D) shows the executives (companies) in the sample with the most tweets as of December 31, 2018. The number of tweets represents the number of tweets we acquired, which may exclude tweets that were deleted.

Table 2: Executives joining Twitter, Determinants model

Variables	**(1)**	**(2)**	**(3)**
Executive age		-0.048***	-0.048***
		(-27.69)	(-27.39)
Female		0.139***	0.112**
		(3.19)	(2.55)
Extraversion		0.624***	0.595***
		(23.51)	(22.36)
SEC Regulation	0.138*	0.150*	0.146*
	(1.69)	(1.82)	(1.78)
Size	-0.098***	-0.143***	-0.193***
	(-10.67)	(-15.03)	(-18.59)
ROA	-1.189***	-1.169***	-0.915**
	(-3.27)	(-3.18)	(-2.46)
MTB	0.027***	0.015*	-0.012
	(3.17)	(1.76)	(-1.35)
Debt	0.149***	0.100**	0.063
	(2.93)	(1.96)	(1.22)
Litigation risk	1.375***	1.098***	0.852***
	(10.16)	(8.07)	(6.20)
log(Followers, Firm)			0.077***
			(8.22)
log(Following, Firm)			0.037***
			(3.62)
log(Total tweets, Firm)			-0.050***
			(-4.16)
Days since firm joined			0.009***
			(4.43)
Joined Twitter, Firm			-0.491***
			(-9.48)
Constant	-4.074***	-3.563***	-2.819***
	(-29.79)	(-19.91)	(-15.18)
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 (1) 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 $p < 0.10$.

Table 3. Univariate statistics, daily sample of executives on Twitter

Variables	Mean	S.D.	p25	p50	p75
During trading hours					
Financial tweets, Executive	0.00135	0.0438	0	0	0
Non-fin business tweets, Executive	0.113	1.43	0	0	0
Other tweets, Executive	0.0229	0.315	0	0	0
Financial tweets, Firm	0.0181	0.164	0	0	0
Non-fin business tweets, Firm	3.41	31.0	0	0	2
Other tweets, Firm	1.07	18.4	0	0	0
Outside trading hours					
Financial tweets, Executive	0.00224	0.0696	0	0	0
Non-fin business tweets, Executive	0.254	6.59	0	0	0
Other tweets, Executive	0.0536	1.01	0	0	0
Financial tweets, Firm	0.0212	0.201	0	0	0
Non-fin business tweets, Firm	5.26	81.7	0	0	2
Other tweets, Firm	1.78	87.4	0	0	0
Executive characteristics					
Executive age	52.21	7.01	48	52	57
Female	0.0882	0.284	0	0	0
Extraversion	4.01	0.515	3.90752	3.91	4.352096
CEO	0.665	0.472	0	1	1
CFO	0.342	0.474	0	0	1
Firm characteristics					
Size	7.700	1.800	6.38405	7.434	8.746433
ROA	0.008	0.033	.0017612	0.010	.0208238
MTB	1.725	1.829	.5811759	1.106	2.260437
Debt	0.559	0.258	.3766385	0.550	.7227702
Twitter account characteristics					
Joined Twitter, Firm	0.761	0.426	1	1	1
log(Followers, Executive)	3.120	3.704	0	1.609	5.937536
log(Following, Executive)	2.491	2.662	0	1.792	5.003946
log(Total tweets, Executive)	0.569	1.877	0	0	0
log(Followers, Firm)	6.734	4.795	0	7.905	10.04876
log(Following, Firm)	4.730	3.354	0	5.820	7.182352
log(Total tweets, Firm)	5.526	3.931	0	6.940	8.704751

Note: This table presents univariate statistics of the sample of trading day-executive-firm observations restricted to trading days where the executive had joined Twitter that day or prior. There are 509,756 observations for each measure.

Table 4: Executive response on Twitter to information events

Event	*Time of tweeting*	Financial tweets, Executive (1)	Non-fin business tweets, Executive (2)	Other tweets, Executive (3)
Panel A: Earnings events				
	Tweets before trading	2.37***	0.081	0.118
		(18.63)	(1.06	(1.40)
	Tweets during trading	1.76***	0.226***	0.192**
		(9.97)	(3.93)	(1.96)
	Tweets after trading	1.07***	0.106	0.040
		(5.61)	(1.35)	(0.42)
Panel B: 10-K or 10-Q filings				
	Tweets before trading	1.61***	0.102	0.113
		(9.52)	(1.11)	(1.23)
	Tweets during trading	1.48***	0.057	0.095
		(7.68)	(0.97)	(0.94)
	Tweets after trading	0.896***	0.021	0.036
		(4.43)	(0.24)	(0.37)
Panel C: 8-K filings				
	Tweets before trading	0.714***	-0.020	-0.001
		(6.45)	(-0.42)	(-0.02)
	Tweets during trading	0.599***	0.005	-0.043
		(44.66)	(0.14)	(-0.78)
	Tweets after trading	0.890***	-0.085	0.001
		(8.23)	(-1.62)	(0.02)

Note: This table presents the results of regression equation (2) on the daily sample of executives (509,756 observations) using Poisson pseudo maximum likelihood (PPML) regression. The dependent variable is the number of tweets posted by a manager during a given period, where column (1) examines counts of financial tweets, column (2) examines counts of non-financial business tweets, and column (3) examines counts of 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 occur in one of three windows: 1) *before trading* ranges from the close of the prior trading day until the open of the current trading day, 2) *during trading* covers the trading hours of the current trading day from open to close, and 3) *after trading* ranges from the close of the current trading day to the open of the next trading day. 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), in a PPML regression including all controls along with fixed effects for Firm, Executive, Year, and Month. Z statistics are presented in parentheses, and significance is denoted as follows: *** denotes $p < 0.01$, ** denotes $p < 0.05$, and * denotes $p < 0.10$.

Table 5: Market response to executive tweets

Variables	|MMR$_t$| (1)	(2)	(3)	(4)	(5)
Executive tweet measures					
Financial tweets, During trading	0.003***		0.002***	0.002**	0.002**
	(2.98)		(2.40)	(2.07)	(2.12)
Financial tweets, Before trading		0.002***	0.002**	0.001*	0.003***
		(3.59)	(3.19)	(1.77)	(3.25)
Non-fin business tweets, During trading	0.000		0.000	0.000	-0.000
	(0.60)		(0.20)	(0.39)	(-0.25)
Non-fin business tweets, Before trading		-0.000	-0.000	-0.000	0.000
		(-1.57)	(-1.45)	(-0.91)	(1.43)
Other tweets, During trading	-0.000		-0.000	-0.000	-0.000
	(-1.33)		(-1.48)	(-1.32)	(-0.27)
Other tweets, Before trading		0.000	0.000	0.000	0.000
		(1.10)	(1.12)	(1.04)	(0.28)
Firm tweet measures					
Financial tweets, During trading	0.001***		0.000*	0.000	0.000*
	(3.10)		(1.71)	(0.78)	(1.66)
Financial tweets, Before trading		0.002***	0.002***	0.001***	0.002***
		(10.01)	(9.85)	(7.14)	(9.77)
Non-fin business tweets, During trading	0.000		-0.000	0.000	-0.000
	(0.66)		(-0.24)	(0.04)	(-0.25)
Non-fin business tweets, Before trading		0.000	0.000	0.000	0.000
		(0.56)	(0.59)	(0.66)	(0.47)
Other tweets, During trading	-0.000***		-0.000**	-0.000**	-0.000**
	(-3.27)		(-2.08)	(-2.17)	(-1.96)
Other tweets, Before trading		-0.000***	-0.000	-0.000	-0.000
		(-2.91)	(-1.46)	(-0.87)	(-1.56)
Controls	Yes	Yes	Yes	Yes	Yes
Firm event control	No	No	No	Yes	No
Executives all on Twitter	Yes	Yes	Yes	Yes	Yes
Firms all on Twitter	No	No	No	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Executive FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Exec – Firm fin tweets, During, F-test	0.002**		0.002**	0.002*	0.002*

Exec – Firm fin tweets, Before, F-test		0.000	0.000	-0.000	0.000
Adj R-Sq	**0.117**	**0.118**	**0.118**	**0.151**	**0.108**
Observations	**506,548**	**506,548**	**506,548**	**506,548**	**385,568**

Note: This table presents the results of regression equation (3) on the daily sample of executives using a linear regression with high dimensional fixed effects (HDFE). The dependent variable in all panels is absolute market model return on day t. Tweets occur in one of two windows: 1) *before trading* ranges from the close of the prior trading day until the open of the current trading day and 2) *during trading* covers the trading hours of the current trading day from open to close. Columns (3) through (5) include all independent variables for tweet content across both the trading and before trading windows. Column (4) additionally includes a control for firms' important information events, *Firm event*. Column (5) is on the subset of data where both executives and their firms have both already joined Twitter. The "Exec – Firm fin tweets" rows document the results of an F-test between the coefficient on executive financial tweets and firm financial tweets, with the value being the difference between the coefficients. Controls include executive age, firm size, ROA, MTB, debt, firm Twitter account characteristics, and executive Twitter account characteristics. t statistics are presented in parentheses, and significance is denoted as follows: *** denotes $p < 0.01$, ** denotes $p < 0.05$, and * denotes $p < 0.10$.

Table 6: Market response to executive tweets around earnings events

	|MMRt|	
	Announcement during trading	**Announcement before trading**
Variables	**(1)**	**(2)**
Financial tweets, Executive		
Before trading	0.009*	
	(1.69)	
During trading, Before announcement	-0.006	
	(-0.51)	
During trading, After announcement	-0.004	
	(-0.31)	
Before trading, Before announcement		-0.005
		(-0.19)
Before trading, After announcement		0.004
		(0.14)
During trading		0.016**
		(2.41)
Financial tweets, Firm		
Before trading	-0.000	
	(-0.05)	
During trading, Before announcement	-0.010*	
	(-1.71)	
During trading, After announcement	-0.010***	
	(-2.59)	
Before trading, Before announcement		0.002
		(0.51)
Before trading, After announcement		-0.001
		(-0.50)
During trading		-0.001
		(-0.77)
Controls	Yes	Yes
Firm FE	Yes	Yes
Exec FE	Yes	Yes
Year FE	Yes	Yes
Month FE	Yes	Yes

Adj R-Sq	**0.285**	**0.223**
Observations	**1,429**	**6,244**

Note: This table presents the results of regression equation (3) when the sample is restricted to periods around earnings events (earnings announcements or earnings conference calls). Column 1 is on a sample where the earnings event occurred during the trading day. Column 2 is on a sample of trading days where an earnings event occurred between that trading day and the prior trading day. All regressions require executives to be on Twitter and use a linear regression with high dimensional fixed effects (HDFE). The dependent variable in all panels is absolute market model return on day t. Tweets occur in one of two windows: 1) *before trading* ranges from the close of the prior trading day until the open of the current trading day and 2) *during trading* covers the trading hours of the current trading day from open to close. The regressions all include controls for executive age, firm size, ROA, MTB, debt, firm Twitter account characteristics, and executive Twitter account characteristics, along with fixed effects for Firm, Executive, Year, and Month. No firm event control is included, as it is constant throughout these samples. *t* statistics are presented in parentheses, and significance is denoted as follows: *** denotes $p < 0.01$, ** denotes $p < 0.05$, and * denotes $p < 0.10$.

Table 7: Market response mechanism, New information or trust

	|MMRt|			
Variables	**(1)**	**(2)**	**(3)**	**(4)**
Tweets during trading hours, day t				
Financial tweets, Executive	-0.025**		-0.011	
	(-2.22)		(-1.08)	
Financial tweets, Firm	0.001***		0.000*	
	(3.08)		(1.71)	
Tweet similarity	-0.078**		-0.038	
	(-2.23)		(-1.26)	
Similarity undefined	-0.029**		-0.015	
	(-2.41)		(-1.42)	
Financial tweets, Executive ×	0.074**		0.032	
Tweet similarity	(2.26)		(1.14)	
Financial tweets, Executive ×	0.026**		0.012	
No firm tweets	(2.35)		(1.19)	
Tweets before trading hours, day t				
Financial tweets, Executive		-0.014***		-0.009**
		(-3.17)		(-2.28)
Financial tweets, Firm		0.002***		0.001***
		(10.06)		(7.23)
Tweet similarity		-0.026		-0.015
		(-1.33)		(-0.82)
Similarity undefined		-0.008		-0.004
		(-1.12)		(-0.61)
Financial tweets, Executive ×		0.046***		0.030**
Tweet similarity		(3.30)		(2.33)
Financial tweets, Executive ×		0.017***		0.012**
No firm tweets		(3.41)		(2.47)
Controls	Yes	Yes	Yes	Yes
Firm event control	No	No	Yes	Yes
Executives all on Twitter	Yes	Yes	Yes	Yes
Firms all on Twitter	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Executive FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Adj R-Sq	**0.108**	**0.108**	**0.147**	**0.146**
Observations	**385,568**	**385,568**	**385,568**	**385,568**

Note: This table presents the results of regression equation (4) on a daily sample where executives and their firms are both on Twitter. The linear regressions use high dimensional fixed effects (HDFE) while including interactions between the number of executives' financial tweets with both *Tweet similarity* and *No firm tweets*. *Tweet similarity* is the similarity between the executive's financial tweets on a given day and the firm's tweets in the 48 hours directly preceding the tweet (up to the second before the executive's tweet). *No firm tweets* is an indicator for if the firm did not release any tweets in the 48 hours leading up to all of the executive's financial tweets. The dependent variable is absolute market model return on day t. Tweets occur in one of two windows: 1) *before trading* ranges from the close of the prior trading day until the open of the current trading day and 2) *during trading* covers the trading hours of the current trading day from open to close. The regressions all include controls for executive age, firm size, ROA, MTB, debt, firm Twitter account characteristics, and executive Twitter account characteristics, along with fixed effects for Firm, Executive, Year, and Month. *t* statistics are presented in parentheses, and significance is denoted as follows: *** denotes $p < 0.01$, ** denotes $p < 0.05$, and * denotes $p < 0.10$.

Table 8: Market response mechanism, Partitioned sample analysis

Panel A: Tweets before trading hours

	|MMR$_t$|					
	Firm size		**Institutional Ownership**		**Exec vs firm followers**	
Variables	**≥ median**	**< median**	**≥ median**	**< median**	**Exec ≥ Firm**	**Exec < Firm**
Financial tweets, Executive	-0.011***	-0.024	-0.012**	-0.003	-0.007	-0.013
	(-2.85)	(-0.63)	(-2.27)	(-0.21)	(-1.34)	(-0.84)
Financial tweets, Firm	0.001***	0.002***	0.002***	0.001***	0.001	0.001***
	(6.94)	(3.88)	(5.39)	(4.85)	(1.38)	(6.91)
Tweet similarity	-0.032*	-0.041	-0.031	0.013	-0.036	-0.022
	(-1.81)	(-0.34)	(-1.48)	(0.24)	(-1.47)	(-0.53)
Similarity undefined	-0.010*	-0.010	-0.009	0.006	-0.013	-0.006
	(-1.70)	(-0.23)	(-1.33)	(0.26)	(-1.59)	(-0.32)
Financial tweets, Executive	0.036***	0.081	0.040**	0.012	0.023	0.043
× Tweet Similarity	(2.84)	(0.76)	(2.28)	(0.33)	(1.26)	(1.15)
Financial tweets, Executive	0.011**	0.033	0.014**	0.013	0.006	0.021
× No firm tweets	(2.58)	(0.84)	(2.25)	(0.79)	(1.11)	(1.27)
Adj R-Sq	**0.153**	**0.129**	**0.145**	**0.156**	**0.143**	**0.148**
Observations	**202,732**	**182,836**	**214,073**	**171,495**	**36,713**	**348,855**

Panel B: Tweets during trading hours

	|MMRt|					
	Firm size		**Institutional ownership**		**Exec vs firm followers**	
Variables	**≥ median**	**< median**	**≥ median**	**< median**	**Exec ≥ Firm**	**Exec < Firm**
Financial tweets, Executive	-0.013	-0.025**	0.001	-0.032	-0.017	-0.043**
	(-1.12)	(-2.17)	(0.03)	(-1.50)	(-1.55)	(-2.12)
Financial tweets, Firm	0.000**	0.000	0.000	0.000**	0.001	0.000
	(2.05)	(0.57)	(0.81)	(1.99)	(1.31)	(1.43)
Tweet similarity	-0.037	-0.088***	0.007	-0.103*	-0.040	-0.118**
	(-1.03)	(-2.98)	(0.10)	(-1.87)	(-1.03)	(-2.11)
Similarity undefined	-0.013	-0.041**	0.001	-0.045	-0.009	-0.055**
	(-0.99)	(-2.40)	(0.04)	(-1.64)	(-0.68)	(-2.45)
Financial tweets, Executive	0.041	0.063***	-0.000	0.082*	0.058*	0.099*
× Tweet similarity	(1.24)	(2.84)	(-0.00)	(1.73)	(1.83)	(1.88)
Financial tweets, Executive	0.015	0.024**	0.000	0.037*	0.016	0.047**
× No firm tweets	(1.31)	(2.07)	(0.00)	(1.68)	(1.47)	(2.29)
Adj R-Sq	**0.153**	**0.128**	**0.145**	**0.155**	**0.143**	**0.148**
Observations	**202,732**	**182,836**	**214,073**	**171,495**	**36,713**	**348,855**

Note: This table presents the results of regression equation (4) on subsamples of the daily sample where executives and their firms are both on Twitter. Panel A presents the results of the partitioned sample tests for financial tweets posted during the period from the close of the prior trading period to the open of the current trading period. Panel B presents the results of the partitioned sample tests for financial tweets posted during the trading period from open until close. The first two (second two) columns of both panels present a median split on Firm size (institutional ownership) based on the median in the full sample of firms in the study. The final two columns present a split on whether the executive has at least as many followers as the firm or not. The linear regressions use high dimensional fixed effects (HDFE) while including interactions between the number of executives' financial tweets with both *Tweet similarity* and *No firm tweets*. *Tweet similarity* is the similarity between the executive's financial tweets on a given day and the firm's tweets in the 48 hours directly preceding the tweet (up to the second before the executive's tweet). *No firm tweets* is an indicator for if the firm did not release any tweets in the 48 hours leading up to all of the executive's financial tweets. The dependent variable is absolute market model return on day t. The regressions all include controls for executive age, firm size, ROA, MTB, debt, firm events, firm Twitter account characteristics, and executive Twitter account characteristics, along with fixed effects for Firm, Executive, Year, and Month. *t* statistics are presented in parentheses, and significance is denoted as follows: *** denotes $p < 0.01$, ** denotes $p < 0.05$, and * denotes $p < 0.10$.