Executive Tweets

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

Wenli Huang
Assistant Professor of Accounting
School of Accounting and Finance
Hong Kong Polytechnic University
wlhuang@polyu.edu.hk

Hai Lu
Professor of Accounting
Rotman School of Management
University of Toronto
Hai.Lu@Rotman.Utoronto.Ca

This draft: January 23, 2019

We gratefully acknowledge the helpful suggestions of Elizabeth Blankespoor, Paul Koch, Ties de Kok, Ed deHaan, Sunghan Lee, Dawn Matsumoto, Xiumin Martin, Khim Kelly and the seminar participants of Iowa State University, Singapore Management University, University of Central Florida, 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.

Executive Tweets

Abstract

We examine the tweeting behavior of S&P 1500 firms' executives (CEOs and CFOs) on Twitter and its consequences. We find that following the release of the U.S. Securities and Exchange Commission's 2013 report on social media usage by corporations and executives, executives from firms with high litigation risk are less likely to join Twitter. We also document that executives tweet financial information related to their firms and time these tweets to firms' major financial and non-financial events, and that investors respond to executive tweets in addition to firm tweets. Using an innovative construct measuring the content similarity between executive tweets and firm tweets, we find evidence consistent with the view that investors trust similar information from executive Twitter accounts more than information from firm Twitter accounts.

***Keywords*:** Social media; executives; dissemination; Twitter; executive effort
***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 126 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. Several recent high profile individual social media posts have significantly affected the perception of people on individual tweeting behavior.[2] Yet, we know little about individuals' tweeting behavior in the corporate world. In this study we fill this gap in the literature, examining executive tweets. Specifically, we ask the following research questions: Does the SEC's guidance on using social media as an information disclosure channel issued in April 2013 affect the use of Twitter by executives? Do executives time their business related tweets with corporate events? And do these executive tweets impact firm stock price and provide information in addition to firms' own tweets?

Actions of individuals on social media in recent years have caught the attention not just of investors, but also of the media and regulators. For example, 243 press articles on CEO tweets appeared in media in the first four months of 2019.[3] Netflix's CEO, Reed Hastings, posted a message on Facebook on July 3, 2012 that Netflix customers viewed more than 1 billion hours of video content a month. The post led to a 6.2% increase in Netflix's stock price and subsequent

---

[1] As of Q4 2018, per Twitter's 2018 Q4 Shareholder Letter.
[2] For example, Reed Hastings' Facebook post triggered an SEC review of corporate use of social media for disclosure; Elon Musk's unjustified tweet brought him a litigation case which forced him out from the chairman position at Tesla; Donald Trump's tweets have changed the way of communication between the President of the United States and the general public.
[3] Based on a Factiva search for "CEO" and "tweet" in the headline of an article, excluding web content.

investigation by the U.S. Securities and Exchange Commission (SEC). The SEC concluded on April 2nd, 2013 that social media accounts, both of firms and executives, are "public enough" to disclose information while maintaining compliance with Regulation Fair disclosure. The SEC's report may consequently have impacted the incentives of executives' joining Twitter and their tweeting behaviors. While the report clears the path towards legitimate disclosure on social media, it may change the executives' perception about the litigation risk of tweeting. Ultimately, the answer to our first question depends on the tradeoff between the benefits of having a new information disclosure channel and the costs associated with the disclosures and litigation.

Executive Twitter accounts and firm Twitter accounts are different. While the latter is expected to be filled with business related tweets, executives could devote their accounts exclusively for personal use. In addition, while firms filter information and decide what to post on Twitter, executives may further filter what to tweet through their personal accounts. A number of recent studies show whether firms strategically disseminate information on social media 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., 2019), however, few empirical studies examine executives' tweeting behavior despite the fact that individual Twitter accounts have become more popular and gained visibility. Thus, it is interesting to explore the incentives, strategic behavior, and consequences of executives tweeting. The answers to the second and third research questions can help to decide whether executive tweeting matters and if executive tweeting behavior should be regulated.

One common and important question is whether executive tweets provide additional information beyond firm tweets or if executive tweets are more credible signals. Experimental studies show that executive tweets play a significant role in influencing investors' trust on firm disclosures (Elliott et al. 2018; Grant et al. 2018), and we examine this argument using large sample archival data in this study. Based on a new algorithm developed at Google (Cer et al. 2018), we construct a similarity measure which compares the meaning of executives' and firms' tweets. We use the new measure as a proxy for new information and for the degree of trust, where high (low) similarity score indicates less (more) new information and more (less) trustable executive tweets. We then test whether and how the sensitivity of market response to executive tweets varies with this similarity score.

Our findings show that although the SEC's report following the investigation of Reed Hastings' 2012 post does not have a significant effect on the likelihood of executives joining Twitter for the firms with low litigation risk, executives from the firms with high litigation risk firms are less likely to join Twitter after the report. Our difference-in-differences test shows that the trend for the number of CEOs joining Twitter after the release of the SEC report is affected by litigation risk, controlling for other firm's characteristics and executive's personal attributes. A mixture of demographic and firm characteristics such as age, gender, extraversion, firm size, and the number of followers the firm has on Twitter appear to drive the decision of joining Twitter from 2011 through 2016.

We then turn our attention to what executives post on Twitter, examining the composition of financial information, business-related non-financial information, and non-business information. We find strong evidence that executives do tweet about financial-relevant information when firms have major events regardless of whether these events are financial or non-financial in nature. Meanwhile, executives tweet more business-related non-financial information only when firms have non-financial related events. Financial events include earnings announcements and earnings conference calls and 10-K and 10-Q filings, and non-financial events include 8-K filings, general press releases, and news articles. The evidence suggests that executives time tweets when disseminating business information on Twitter.

Our findings further suggest that stock prices react to executives' tweets. On the next day following executive tweets, the stock market reacts to executive tweets even when controlling for firm tweets and corporate events. The market response is not significant on the day of executive tweets and two days after executive tweets. Moreover, we document that the similarity between executive tweets and firm tweets positively affects the relation between executive tweets and abnormal market returns, i.e., when executive tweets and firm tweets are similar, investors react more strongly, consistent with the findings in Elliott et al. (2018) that investors trust CEOs more when CEOs disseminate firms' news from social media accounts. The evidence seems to suggest that investors do not value more information in executive tweets when the content of these tweets are significantly different from firm tweets.

Our paper contributes to the burgeoning research in finance and accounting on social media. Our paper is the first study in the literature using a large sample to examine the drivers of executives joining Twitter and the effect of the regulator's action in 2013. Although the SEC just restates the existing rules and clarifies the legitimacy of disclosing information on social media, executives' perception of litigation risk may be altered by the SEC's announcement. We document that executives appear to be willing to tweet business information about their firms; they are more likely to tweet around the time when there are significant corporate events such as earnings announcements, earnings conference calls, 10-K and 10-Q filings, 8-K filings and releases of news articles. More importantly, we not only show that the market responds to executive tweets, we prove – using an innovative similarity measure – that the market appears to respond due to trust of the executives, responding more to executive tweets that are more similar to firm tweets in content.

Section 2 discusses the literature and presents our hypotheses. Section 3 describes our data sources, sample, and research design. Sections 4 and 5 present empirical results and additional tests. Section 6 concludes.

2 Literature and Hypothesis Development

2.1 Literature review

Over the past decade, 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. The extent of use of Twitter by firms as compared to other social media channels is discussed in Jung et al. (2018), which 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.

Executive and firm disclosures are endogenously linked, and the same set of incentives for executives joining Twitter may also drive the creation of firm Twitter accounts. Yet, the incentives are also different. Firms' Twitter accounts are managed by firms' public relations teams and tweeting must follow corporate internal control procedures, whereas executives Twitter accounts are likely to be more flexible. Executives have more control but share more personal responsibility. Studying executive tweeting behavior is thus related to the emerging literature on firms' use of Twitter. A popular strand of literature focuses on predicting firm stock performance by leveraging content 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. They find that tweet sentiment appears to be associated with stock returns. Curtis et al. (2016) examine 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) find that information contained on Twitter helps predict both firm-level stock returns and future earnings.

Another theme of research examines the extent to which firms disseminate information on Twitter as well as the consequences of such dissemination. Blankespoor et al. (2014) examine the impact of technology firms disseminating hyperlinks to earnings announcement press releases via Twitter, finding 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) find 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. Crowley et al. (2018) also provide large-sample evidence on firms' dissemination strategies on Twitter. They find that firms disseminate more financial information on Twitter around earnings announcements, 10-K and 10-Q filings, and 8-K filings if the information contained in the firms' other disclosures is significantly positive or negative.

A separate strand of literature 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) provide 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 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 individuals' and companies' accounts, an executive may post on Twitter for intrinsic or image-related benefits, or they may still post on Twitter for company-related reasons. The decision of having a personal Twitter account is also related to age, gender or other executives' personal features such as extraversion.

2.2 Hypothesis development

Ex ante, executives may behave like any other individuals on Twitter, using Twitter for their own personal enjoyment. However, it is clear that some executives instead choose to represent their firms, releasing information that is in line with their firm's disclosures to aid in strategic dissemination of corporate information. As such, it is interesting to examine whether executives would tweet information that is potentially useful to other parties.

If executives do have a desire to strategically disseminate useful information to investors, they would encounter the unclear legal status of disclosing corporate information on their personal Twitter accounts and potential litigation risk. 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

[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

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's primary conclusion is that the 2008 SEC guidance is applicable and that executives posting investor-relevant information on social media *is not* a violation of Reg FD.[5]

One would naturally ask whether the SEC report would drive the adoption of Twitter by executives. The SEC report makes explicitly clear that disclosing information on social media is legal, which may solicit more executives to take advantage of interactive nature of Twitter when disseminating information. Given the SEC's conclusion that social media use is consistent with the 2008 guidance, it is possible that some firms and executives would have no issue with disclosing investor-relevant information on social media before and after the 2013 SEC report. Thus, there is a credible null of the 2013 SEC report having no impact on executives' behavior on social media. However, since the SEC advises firms and executives to inform investors explicitly that they are using social media as a disclosure channel, it may increase the perceived litigation risk for firms and executives if they follow the SEC's advice. Litigation risk on executives' tweets would negatively affect the likelihood of executives adopting Twitter, so empirically we may observe a decrease of executives joining Twitter, particularly for the executives of firms with high litigation risk following the release of the 2013 SEC report. We state our first hypothesis in alternative form:

Hypothesis 1: *The likelihood of executives joining Twitter decreases with the litigation risk of firms after the release of the 2013 SEC report.*

[5] The SEC does, however, suggest informing investors that a certain social media account is used for disclosure or dissemination of important information for investors. An example of such as disclosure for Twitter's 2019 Q1 press release is as follows "Twitter has used, and intends to continue to use, its Investor Relations website and the Twitter accounts of @jack, @nedsegal, @twitter and @TwitterIR as means of disclosing material non-public information and for complying with its disclosure obligations under Regulation FD." (Available at: https://s22.q4cdn.com/826641620/files/doc_news/events/2019/04/Q1'19-Earnings-Date-Announcement.pdf)

An increase or decrease in executive activities on Twitter shows the degree of desire by executives to post investor-relevant information on social media. If executives tweet for intrinsic utility (Toubia and Stephen 2013) or due to the pressure of peers on Twitter (Lin and Lu 2011), executives are less likely to choose the timing of their tweets with respect to firm disclosures. However, like firm tweets, executives would strategically time tweets if they intend to maximize the benefits of executive tweeting for their firms or themselves. We expect that executives react to various events that their company is experiencing. For instance, if managers desire to post investor-relevant information on Twitter, then the release of an earnings announcement, holding an earnings conference call, or release of 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 and press releases, should drive financial as well as broader business-related dissemination or disclosure on Twitter by executives, as should news about the firm covered in the press. If executives do not want to post about their firms, we would expect their behavior on Twitter not to respond to such important events. This leads to our second hypothesis:

> ***Hypothesis 2***: *Executives are more likely to post financial tweets on days with all major corporate events and tweet more in general on days with non-financial related corporate events.*

Our next question is whether investors find executives' tweets to provide incremental information after they see firm tweets. While there are examples of social media posts that have moved the market, such as Reed Hastings' 2012 Facebook post on the number of hours watched by customers or Elon Musk's 2018 tweet about taking Tesla private, it is possible that the majority of information posted by executives is largely the same as what is already available elsewhere. As such, we might expect the information to have no effect on the market. On the other hand, there is evidence showing that even tweets by investors are able to predict market movements (Bollen, et al. 2011; Mao et al. 2012; Sprenger et al. 2014), and it is natural to expect an executive to be able to post more useful information than most investors. Furthermore, even repeated dissemination of the same information has been shown to affect stock prices (Tetlock 2011). As such, 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 related tweets. This expectation leads to our third hypothesis:

> ***Hypothesis 3****: The market responds to executive financial tweets in addition to firm financial tweets.*

The market may respond to executive tweets for different reasons: Executive tweets may provide new information that is incremental to the information in firm tweets, or executive tweets may not provide new information but instead change the reliability of the information as tweets by executives have a more human element to them than firm tweets. An experimental study by Elliott et al. (2018) 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. This evidence suggests that the information communication channel is important even when information content remains unchanged. To separate the two possible mechanisms, we propose a unique hypothesis examining the effect of content similarity between executive tweets and firm tweets. We discuss the methodology and construction of the measure in Section 3.2.1. The similarity score is expected to be low when executive tweets have new information, i.e., the content of executive tweets deviates from firm tweets. The score should be high when the content of executive tweets is similar to that of firm tweets. The direction of the effect of similarity suggests which mechanism is supported. We thus present our fourth and final hypothesis consistent with the view that the market responds to CEO tweets due to investor trust:

Hypothesis 4*: The market responds more strongly to executive tweets with content similar to firm tweets.*

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 S&P 1500 index between January 1, 2012 and September 30, 2016. Twitter handles for companies and CEOs were identified between September and October 2016, while Twitter handles for CFOs were identified in April 2017. In total, we have identified 1,433 firm accounts and 200 executive accounts. 93 executive accounts are excluded from our sample, as the executives did not release any tweets while they were CEOs or CFOs of S&P 1500 firms or had their accounts set to private, and 133 firm accounts were excluded due to having no tweets or being set to private. Our tweet sample is based on a mix of data from GNIP and the Twitter API 2.0. Specifically, we used the Twitter API 2.0 to download all publicly available tweets associated with each Twitter ID in October, 2016. Public access is limited to the 3,200 most recent tweets per account. There were 614 firm and 3 executive accounts which posted more than 3,200 tweets between January 2012 and September 2016; for these companies and executives, we purchased a complete set of tweets from GNIP, a data provider and subsidiary of Twitter. We then collected 2017 and 2018 data by continuously downloading the data using the Twitter API 2.0.

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 call times, WRDS SEC Analytics Suite for 10-K, 10-Q, and 8-K times, Ravenpack PR Edition for Press release times, and Ravenpack Dow Jones Edition for News article times and content.

To capture executive personality traits we follow Green et al. (2019) and examine conference call transcripts from Thomson Reuters Street Events, examining all calls 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 September 30, 2016, 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 6.98 million (111,942) firm-executive-trading day (fiscal quarter) observations.

3.2 Measure construction

A key difficulty and feature of our data is that nearly all the data (tweets and all information events) are tracked to the second of announcement. As such, we standardize all data by assigning each tweet or event to an NYSE trading day. If a tweet or event occurs on a trading day and is released prior to 4:30 PM in New York City, we treat that day as the trading day. If the tweet or event occurs after 4:30 PM (and 0 seconds) in New York City, or if the tweet or event occurs on a day where US stock exchanges are closed, we code the trading day to be the next day that US stock exchanges are open. We take care to factor in issues such as the time-zones that data are derived from (generally either New York time 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 by trading day. Tweets are aggregated to the trading day level, as described in Section 3.2. 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, Ng, and Jordan (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. (2018). 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 *non-business*. Financial tweets are likely to be the most informative, as financial information is crucial for investors. 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. Non-business 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.[6] For daily analyses, we aggregate tweets by counting the number of tweets in each category on each trading day.

[6] The topics are hand classified in Crowley et al. (2018). The *financial* category contains 1 topic, the *non-financial business* category contains 42 topics, and the *non-business* category contains 17 topics. Appendix B contains examples of tweets in each category.

In tests examining why executives joined Twitter, we use whether the executive or firm has a Twitter account with at least one tweet as of the beginning of a given quarter as a dependent variable.

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. 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.

For testing Hypothesis 4, we introduce a fine-grained measure of content or meaning of text to the accounting literature, called Universal Sentence Encoder (USE). The USE algorithm, newly 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 accounting, 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 local area. We leverage this feature, demonstrated in Cer et al. (2018), to precisely measure the similarity of executives' tweets with their firms' tweets. Examples of sentences encoded with this algorithm and their respective similarities are provided in Appendix C, along with a more detailed description of our methodology.

To construct our measure, for each executive tweet we identify all tweets by the executive's firm in the 7 days leading up to the executive tweet, precisely up to the second prior to the executive tweet. In these tests, we drop any executive tweets that do not have a corresponding firm tweet in the 7 day window. We then search for the closest firm tweet to the executive tweet.[7] 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 1. We aggregate *tweet similarity* by trading day by taking the mean across all of an executive's tweets of a given type (e.g., financial tweets) each trading day. A higher *tweet similarity* score indicates a tweet or set of tweets that is more consistent with the meaning of the executive's firm's tweets, whereas a lower score indicates tweets that are content-wise different from the executive's firm's tweets.

3.2.2 Executive personality measures

We construct our executive personality measures following Green et al. (2019) using Street Events conference call Q&A sessions. We extract the Q&A portion of all conference calls along with their participants. We then use a mixed fuzzy and manual match to merge the conference call participants (excluding those explicitly listed in the file headers as being external to the firm) to Execucomp by company ticker symbol, year, and name. We allow multiple names from Street Events to match the same Execucomp executive, as executives in the conference calls are often listed by slightly different variants of their name (e.g., with or without a middle name, or with a nickname). We automatically match nicknames using a python parser based on a set of genealogy tables.[8] For any names that we can't match exactly or via nickname, we manually check to see if the conference call participant is identified in Execucomp in the year of the conference call for the

[7] We measure distance using Euclidean distance, and implement the Approximate Nearest Neighbor matching algorithm of Arya and Mount (1993) to efficiently compute exact matches between executive and firm tweets.
[8] The python parser, *nickname-and-diminutive-names-lookup* is available on Github at: https://github.com/carltonnorthern/nickname-and-diminutive-names-lookup

same firm. If we still do not find a match, we then extend our search to the previous and next year in Execucomp. In the end, we are able to match 72.6% of all executives in our sample, including 94% of the executives who joined Twitter.

To calculate extraversion, we follow Green et al. (2019) and use Personality Recognizer, a Java program developed by Mairesse et al. (2007). We use the Support Vector Machine (SVM) with linear kernel model from the Java program to classify the personality of each executive at the Q&A level. The model simultaneously computes all Big-5 personality traits 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. Following Green et al. (2019), we only rely on the calculated personality traits if the executive spoke in at least three conference call Q&A sessions. As we use executive personality as a control variable, we replace any missing personality observations with the sample mean for each trait.

3.2.3 Event measures

The first event we examine is the 2013 SEC report, which occurred on Tuesday, April 2, 2013. To differentiate between observations before and after the SEC report, we construct a variable, *Post SEC*, equal to 1 for April 2, 2013 or later. In quarterly tests, we code *Post SEC* as 1 if the quarter started after April 2, 2013.[9]

The other events are all firm-level events, for which we have intraday data that we map to trading days as we do with tweets. The first event is earnings announcements. Using I/B/E/S data, we create a variable, *Earnings announcement*, equal to 1 if there is an annual or quarterly earnings announcement on the trading day, 0 otherwise. The second measure we create is *Earnings call*, which captures if there is an earnings conference call on a given day, based on Capital IQ's

[9] Our results are unchanged if we define *Post SEC* as the first quarter ending after April 2, 2013, thus including the fiscal quarter during which the 2013 SEC report was released.

conference call schedule. As earnings announcements and earnings conference calls overlap significantly (>60% are on the same trading days), we present results using an aggregate measure of the two, which we call *Earnings event*. 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[10]. Our remaining events are all derived from Ravenpack. For all Ravenpack-based measures we include only the first instance of an article by keeping only the earliest item matching an RP_STORY_ID, and we require an item to have a relevance score of at least 75 (as recommended by Ravenpack). *Press releases* is the count of unique press releases by a firm on a given trading day, using Ravenpack PR Edition. *News articles* is similarly constructed, being the number of unique news articles about a firm on a given trading day, using Ravenpack Dow Jones Edition.[11] [12]

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 (63 trading days), using S&P 500 returns. For tests involving stock returns, we present results using a precise window restricted to only day t+1. This eliminates any concern of reverse causality from executives tweeting due to stock price movements. Studies in accounting often use windows of (-1, +1) or (0, +1) to account for information leakage or expectations of investors about scheduled events. Tweets by executives, however, are not a type

[10] We include this measure as a count as opposed to a binary measure, as we find that a non-trivial amount of days with 8-K filings contain multiple filings (3.7%). In our sample, the most 8-Ks filed on the same trading day is 3, however some S&P 1500 firms whose managers were not on Twitter have filed as many as 5 8-K filings on the same day.

[11] We include our measures of press releases and news articles as counts as these can be significantly clustered together. For press releases, we find that 52.7% of days with a press release contain multiple unique press releases, while 56.4% of days with a news article contain multiple unique news articles.

[12] In Section 5.1, as an additional analysis we disaggregate our measure of news articles into positive and negative news to examine the differential effect of these news types on executive tweeting.

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, we also confirm our results using S&P 500 adjusted returns (equivalent to assuming a beta of 1 for all firm-days) and raw returns.

4 Empirical methodology and results

4.1 Methodology

4.1.1 Executive adoption of Twitter (H1)

To test Hypothesis 1, we use our quarterly sample as described in Section 3.1. We examine the impact of the 2013 SEC report on executives joining Twitter using a logistic model:

$$\begin{gathered}\text{logit}\big(Exec\ on\ Twitter_{t,e}\big) = \alpha + \beta_1 Post\ SEC_t + \beta_2 Legal\ Risk_{t,e} + \\ \beta_3 Legal\ Risk_{t,e} \times Post\ SEC_t + \beta_4 Executive\ characteristics_{t,e} + \beta_5 Time\ trend_t + \\ \beta_6 Financial\ controls_{t,f} + \beta_7 Twitter\ controls_{t,f} + FE(Industry) + \varepsilon_{t,f,e}\end{gathered} \quad (1)$$

Exec on Twitter is our event of interest, and it is 0 until an executive has posted his/her first tweet, after which it becomes 1. Our main variable of interest is the interaction between *Legal Risk* and *Post SEC*, which captures the impact of the 2013 SEC report, and is 1 for quarters that are entirely after April 2, 2013, the date of the report.[13] For results consistent with Hypothesis 1, we would expect β_3 to be negative and significant. This model also serves as a determinants model to explain some of the variation in executives that did and did not join Twitter. As such, we also include the age of the executive (*Executive Age*), as the more frequent presence of younger individuals on social media is well documented.[14] We further include executive gender (*female*), as women have generally been more likely to use social networking websites (though this phenomenon is

[13] Our results are robust to removing the fiscal quarter overlapping the release of the report.
[14] 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.

historically weaker on Twitter).[15] 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.[16] We also include various financial variables used in the prior literature, including firm size (*Size*), return on assets (*ROA*), market to book ratio (*MTB*), and debt to assets ratio (*Debt*). To control for any potential links between firms' Twitter activities and executives joining Twitter, we also include a few measures related to firm tweeting activities: if the firm is on Twitter (*Firm on Twitter*), 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. All variables in the regression are defined in Appendix A.

4.1.2 Executives' tweet determinants (H2)

Next, we address Hypothesis 2 by examining determinants of different categories of tweets (*financial*, *non-financial business*, and *non-business*). For these tests, we restrict to only executive-firm-day observations where *Exec on Twitter* is 1, i.e., days where the executive has a Twitter account and has already tweeted at least once since opening the account. Our main focus will be on the quantity of tweets posted by executives around different events. To implement this, 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

[15] 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.

[16] Our results are robust to the inclusion of all Big-5 personality traits (extraversion, agreeableness, openness conscientiousness, and emotional stability). We only include extraversion in our base model for parsimony.

al. (2019).[17] PPML regression is interpretable like Poisson regression,[18] 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 for Hypothesis 2 is:

$$\begin{gathered} log\left(\mathrm{E}\left(Exec\ topic\ tweets_{t,e} \middle| IVs\right)\right) = \alpha + \beta_1 Event_{t,f} + \beta_2 Firm\ topic\ tweets_{t,f} + \\ \beta_3 Executive\ age_{t,e} + \beta_4 Financial\ Controls_{t,f} + \beta_5 Twitter\ controls_{t,e,f} + \\ FE(Firm, Exec, Year, Month) + \varepsilon_{t,f,e} \end{gathered} \tag{2}$$

Our dependent variable in these regressions is the count of all tweets in a certain category, such as financial tweets. *Event* is an indicator or count variable that is one or more of the event measures discussed in Section 3.2.3. The variable *Firm topic tweets* controls directly for tweets on the same topic and trading day by an executive's firm. 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 executive fixed effect. For other controls, we include the same financial controls as in the tests of Hypothesis 1. We also include the same Twitter controls for firms. We augment these Twitter controls by including the same measures for the executives' Twitter accounts as well (except for the *on twitter* measure, which is always 1 for executives in our sample). Lastly, we include a comprehensive collection of fixed effects: firm, executive (which differentiates between CEO and CFO within firm, as well as changes in management), as well as

[17] The authors of Correia et al. (2019)have made their work publicly available for Stata on SSC via the ppmlhdfe package.

[18] 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.

year and month to capture any linear time trends in tweeting behavior. We use the same controls and fixed effects throughout all regressions testing Hypothesis 2.

4.1.3 Market reaction to executives' tweets (H3)

To address Hypothesis 3, we directly examine stock returns around executive tweets. For these tests, we use the same sample as we used for Hypothesis 2. 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, Hu, and Lu 2016). To test Hypothesis 3, we use a linear regression with HDFE and robust standard errors:[19]

$$\begin{gathered}|MMRet_{window}| = \alpha + \beta_1 Exec\ topic\ tweets_{t,e} + \beta_2 Firm\ topic\ tweets_{t,f} + \\ \beta_3 |MMRet_{t-1}|_{t,f} + \beta_4 Financial\ event_{t,f} + \beta_5 Business\ event_{t,e,f} + \\ \beta_6 Executive\ age_{t,e} + \beta_7 Financial\ Controls_{t,f} + \beta_8 Twitter\ controls_{t,e,f} + \\ FE(Firm, Exec, Year, Month) + \varepsilon_{t,f,e}\end{gathered} \tag{3}$$

As our events are precisely tracked intraday, our primary tests use a window of just day t+1, though we examine all days from day t to day t+5 in an additional test. Our independent variable of interest is *Exec topic tweets*, where a positive and significant coefficient would be consistent with Hypothesis 3. As additional controls for this regression equation, we include the indicators *Financial event* and *Business event* to control for the events tested under our regression tests for Hypothesis 2. *Financial event* is an indicator of if there was an earnings announcement, earning conference call, 10-K filing, or 10-Q filing, while *Business event* is an indicator for 8-K filings, press releases, and news articles. As with our regression tests for Hypothesis 2, we control for the executive's firm's tweets, 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.

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

4.1.4 Market response mechanism (H4)

To examine Hypothesis 4 and the mechanism underlying the market response to executive tweets, we use the same sample and regression structure as for testing Hypothesis 3. Our sample for this test has 226 fewer observations, as we cannot calculate our tweet similarity measure if the executive's firm did not tweet in the 7 days leading up to the executive's tweet. To test the mechanism, we include an interaction of the similarity between an executive's financial tweets on a given day and the executive's firm's tweets in the 7 days leading up to the executive's financial tweet.

$$\begin{gathered}|MMRet_{t+1}| = \alpha + \beta_1 Exec\ topic\ tweets_{t,e} + \\ \beta_2 Tweet\ similarity_{t,f,e} \times Exec\ topic\ tweets_{t,e} + \beta_3 Firm\ topic\ tweets_{t,f} + \\ \beta_4 Tweet\ similarity_{t,f,e} \times Firm\ topic\ tweets_{t,e} + \ \beta_5 |MMRet_{t-1}|_{t,f} + \\ \beta_6 Financial\ event_{t,f} + \beta_7 Business\ event_{t,e,f} + \ \beta_8 Executive\ age_{t,e} + \\ \beta_9 Financial\ Controls_{t,f} + \beta_{10} Twitter\ controls_{t,e,f} + \\ FE(Firm, Exec, Year, Month) + \varepsilon_{t,f,e}\end{gathered} \tag{4}$$

The mechanism can be differentiated based on the sign of β_2. A positive and significant coefficient on this interaction would be consistent with Hypothesis 4 and would indicate that investors react more strongly when executives post financial tweets that are content-wise similar to tweets their firm has posted over the prior seven days. As such, this would support the mechanism being the reliability of the information. Alternatively, a negative and significant interaction 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 mechanism being incremental information.

4.2 Results

4.2.1 Univariate statistics

Figure 1 presents statistics on our sample of Twitter accounts. Panel A presents the percentage of executives in our sample that have Twitter accounts with at least one tweet in each year. Predictably, we find that the number of executives with Twitter accounts increases over time, starting at just 6 executives (0.2%) in 2011 and peaking at 94 executives (2.9%) in 2017. In terms of industries (not tabulated for brevity), we find that communication services and information technology have the highest proportion of executives on Twitter, with 6.67% and 3.41% of unique executives in those industries having a Twitter account. We find that the materials industry has the lowest proportion of executives on Twitter, as no executives from the industry appeared to have identifiable Twitter accounts. In total, our sample of executives with Twitter accounts consists of 107 executives across 318 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. The total number of executives plateaus in 2017 and 2018 as our data collection only captures executives whose accounts were registered prior to May 2017.

Figure 1 Panel B presents the sample of firm Twitter accounts. As with the executive accounts, we find that communications and information technology have the highest rate of adoption of Twitter, at 90.7% and 84.6%, respectively. Likewise, usage of Twitter by firms does increase over time, starting at 48.8% of firms in 2011 and peaking at 74.3% of firms in 2017. Overall, our sample contains 1,272 firms that had a Twitter account. One noticeable difference between executive and firm tweeting is the change in the number of tweets in 2017. While tweets by executives continued to rise in 2017, tweeting by firms decreased in 2017.

Figure 1 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. In the final year of our sample, the distribution of executives' tweets are 0.9% financial, 80.4% non-financial business, and 18.7% non-business.

4.2.2 Executive adoption of Twitter and the 2013 SEC report (H1)

Table 1 presents the univariate statistics of independent variables used for testing Hypothesis 1. 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. Both time variables show a positive difference, consistent with the increase in executive accounts over our sample period as seen in Figure 1 Panel A. We also see that executives on Twitter often come from firms with higher litigation risk.

Regarding executive characteristics we see that all three characteristics are significantly different for executives on Twitter. Consistent with Pew (2018), younger executives are more likely to be on Twitter, with executives on Twitter being 3.8 years younger than those not on Twitter, on average. We also find that executives on Twitter are 77% more likely to be female than executives not on Twitter. Lastly, as expected, we find that extraverted CEOs are more likely to be on Twitter.

Among firm characteristics, we see no difference in firm size or profitability (as measured by ROA) across groups. Executives on Twitter are more likely to work for more growth-oriented firms (with higher market to book ratios) and firms with less debt. 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 the sample by if the executive or firm is on Twitter. When the firm is not on Twitter, its executive is on Twitter only 0.3% of the time, whereas if the firm is on Twitter the likelihood that the executive is on Twitter is over double at 0.8% of the time.

We present our test of Hypothesis 1 in Table 2. For Hypothesis 1, we expect to observe a negative and significant coefficient on the interaction between *Legal risk* and *Post SEC*. As predicted, after the release of the 2013 SEC report, we find that executives at firms with higher litigation risk are less likely to join Twitter as compared to before the 2013 SEC report. Interestingly, we observe no main effect of the 2013 SEC report, suggesting that the report did not lead to an overall increase or decrease in executives joining Twitter. We do however observe a main effect of litigation risk, as the main effect of *Legal risk* is positive and significant. Taken together, these results indicate that executives at firms facing higher litigation risk are more likely to join Twitter, but as the 2013 SEC report also served to inform investors about social media as a formal disclosure channel, this increased scrutiny appears to have tempered these executives' interest in joining Twitter.

The model presented in the last column of Table 2 also provides a determinants model for executives joining Twitter by including executive characteristics in the regression. First, younger CEOs are more likely to be on Twitter. We also find that female and more extraverted CEOs are more likely to be on Twitter. The effect of all three executive characteristics is consistent with the univariate differences discussed above. With respect to firm characteristics, we find that executives at large firms and at firms following more accounts on Twitter are more likely to be on Twitter. As larger firms and those with more followers are likely to be more visible, this evidence may explain the influence of these factors. Lastly, executives in the information technology industry are more likely to join Twitter, likely due to the high-tech nature of the industry.

4.2.3 Executives' tweet determinants (H2)

Univariate statistics for our daily sample restricted to executives on Twitter are presented in Table 3, Panel A. This sample consists of 70,828 executive-firm-days, with executives posting an average of 0.93 tweets per day and their firms posting around 21.0 tweets per day. Among those executives on Twitter, around 63% of days in the sample are by CEOs and 37% are by CFOs, and for approximately 85% 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 non-business. Non-business tweets account for 18% of tweets by executives. Firms follow a similar pattern where non-financial business tweets are still the most common, followed by non-business tweets.

Our tests of Hypothesis 2, following equation (2), are presented in Table 4. In Panel A, we examine the impact of earnings announcements and earnings conference calls on executive tweets. We observe a large increase in the number of financial tweets posted around these events, with no increase in any other category. Given the financial nature of earning announcements and earnings conference calls, this presents strong evidence for Hypothesis 2.[20]

Panel B presents results for SEC filings. Consistent with our expectations, 10-K and 10-Q filings lead to an increase in executives posting financial information on Twitter with no increase in other types of tweeting. On the other hand, as 8-K filings are more broad-focused, we find that 8-K filings lead to an increase in posting of every category of tweet. Again, these results are consistent with Hypothesis 2.

[20] Our results are consistent and robust when separately examining the impact of earnings announcements or earnings conference calls.

Echoing the results for 8-K filings, Panel C of Table 4 presents the results of our press release test. Like 8-K filings, press releases can contain many different types of disclosures or dissemination, and consequently appear to increase all categories of tweeting by executives. Similarly, Panel D shows that executives generally react to the amount of news coverage they receive. This test shows that executives also respond to information events that are external to the firm.

Overall, the findings in Table 4 present strong results in favor of Hypothesis 2. We find evidence that executives' tweeting behavior responds to a wide variety of information events, including both voluntary and mandatory events as well as both internal and external events. Overall, the results show that executives post information such that it is timed to major firm information events.

4.2.4 Market reaction to executives' tweets (H3)

Given the results for Hypotheses 2, it appears credible that executive tweets could contain useful information for investors. To test Hypothesis 3, we run regression equation (3) by tweet type and present the results in Table 5. When we examine financial tweets in the first column, we see a strong positive coefficient for both executive tweets as well as firm tweets. For executive tweets, we observe that an increase of 1 financial tweet leads to an increase in absolute abnormal return on day t+1 of 0.3%. For firm tweets, we observe a similar pattern, but with less economic significance (an increase of 0.04% in absolute abnormal return per tweet). Overall, each financial tweet by an executive leads to 6.83 times the stock price movement of a financial tweet by a firm. When we consider the total amount of financial tweets released by executives and firms, the market reaction to executive tweets *in aggregate* is higher for executive tweets, as there is 1 executive financial tweet for every 6.56 firm financial tweets, but each executive financial tweet has 6.83

times the market reaction of a firm financial tweet. Thus, it appears that financial tweets by executives provide a significant amount of useful information to market participants. However, we find relatively little reaction to non-financial business and non-business tweets by executives and firms, indicating that most useful information to investors is contained only in executives' financial tweets.[21]

To examine exactly when the stock price reaction occurs, Table 6 presents the same test for financial tweets as Table 5 for varying horizons from day t to day t+5. On the day of a tweet by an executive we observe no statistically significant movement, and by day t+2 we also observe no movement in the stock price. As such, it appears that the majority of the reaction to executive tweets is taking place in the trading day following the tweet.

4.2.5 Market response mechanism (H4)

Table 7 presents the results for our test of Hypothesis 4 following regression equation (4). We see a positive and significant coefficient on the interaction between *Tweet similarity* and financial tweets posted by executives.[22] This evidence supports the mechanism of reliability, as it means that investors react more strongly when investors post financial information that is more similar to the information previously posted by their firm. Adding the interaction completely subsumes the main effect of executive's financial tweets, suggesting that reliability is the primary mechanism leading to investor reaction to executive tweets. Furthermore, executives tweeting financial information that is more similar to the executive's firm's tweets is also associated with a stronger reaction to the firm's tweets. This suggests that executives are more likely to tweet similar

[21] As these three models together could be construed as testing a joint hypothesis of 3 statistical tests, we note that our presented result for *financial* tweets is still statistically significant at the $p<0.01$ level after applying a Bonferroni correction.

[22] 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.

information when the executives observe stronger market responses to firm tweets. Overall, the findings support Hypothesis 4.

5 Additional tests

5.1 Positive versus negative news

In our tests of Hypothesis 2, we examine the number of news articles released by Dow Jones owned news sources. To further our understanding of the nature of news, we categorize news articles into negative, positive, or neutral based on the nature of the event using Ravenpack's entity mapping file.

In untabulated tests, we examine the impact of positive and negative news articles on executive tweets. We find that executives tweet financial information as well as non-financial business information around both positive and negative news articles. Interestingly, we find that the increase in non-business tweets around news articles (as documented in Table 4 Panel D) is driven entirely by negative news articles. Around positive news executives increase only financial and non-financial business tweets, whereas around negative news executives increase all types of tweeting. A possible explanation for this result is that executives may be trying to distract from bad news by also tweeting irrelevant content.

5.2 CEO Accounts

As a robustness check, we have re-run all analyses restricting to just CEO accounts. Our sample is consequently reduced to 76 executives on Twitter spanning 692 executive-firm-quarters.

In our test of Hypothesis 1, our primary result is the same – executives at higher litigation risk companies are less likely to join Twitter after the 2013 SEC report although we do observe a main effect of the SEC report, i.e., CEOs are more likely to join Twitter after the report was released. In our tests of Hypothesis 2, our results are consistent for all four event-types examined.

Our results are also identical for the extension discussed in Section 5.1. For the market tests examining Hypothesis 3, we again find consistent results with approximately the same magnitude as well. For our test of Hypothesis 4, we again find consistent results. In total, the results of this study are all robust to examining only CEOs.

6 Conclusion

This paper examines the tweeting behavior of executives. We find that the primary effect of the 2013 SEC report on executives was to decrease the likelihood of joining Twitter by executives at high litigation risk firms. We then examine whether executives tweet around important financial and business disclosures. We show that executives post financial-related tweets around important financial events including earnings announcements, earnings conference calls, and 10-K and 10-Q filings. We also document that executives post both financial and non-financial business-related information on Twitter around more general information events for their firms, such as 8-K filings, press releases, and news articles. We then 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. This reaction is mostly concentrated in the trading day following the tweets. 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, showing that the mechanism is the increased reliability of the information coming from the executives.

References

Arya, S., and D. M. Mount. 1993. Approximate Nearest Neighbor Queries in Fixed Dimensions. In *Proceedings of the Fourth Annual ACM/SIGACT-SIAM Symposium on Discrete Algorithms*: 271–280.

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

Blankespoor, E., G. S. Miller, and H. D. White. 2014. The Role of Dissemination in Market Liquidity: Evidence from Firms' Use of Twitter™. *Accounting Review* 89 (1): 79–112.

Blei, D. M., A. Y. Ng, and M. I. Jordan. 2003. Latent Dirichlet Allocation. *J. Mach. Learn. Res.* 3 (March): 993–1022.

Bollen, J., H. Mao, and X. Zeng. 2011. Twitter Mood Predicts the Stock Market. *Journal of Computational Science* 2 (1): 1–8.

Brown, N. C., R. M. Crowley, and W. B. Elliott. 2020 (Forthcoming). What Are You Saying? Using Topic to Detect Financial Misreporting. *Journal of Accounting Research*.

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

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

Correia, S. 2016. A Feasible Estimator for Linear Models with Multi-Way Fixed Effects. Working paper, Duke University. Available at: http://scorreia.com/research/hdfe.pdf.

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

Crowley, R. M., W. Huang, and H. Lu. 2018. Discretionary Dissemination on Twitter. Working paper, Singapore Management University, Hong Kong Polytechnic University, and University of Toronto. Available at: https://papers.ssrn.com/abstract=3105847.

Crowley, R. M., W. Huang, H. Lu, and W. Luo. 2019. Do Firms Tweet Social Responsibility? Evidence from Machine Learning Analysis. Working paper, Singapore Management University, Hong Kong Polytechnic University, University of Toronto, and Peking University.

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

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

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

Grant, S., F. Hodge, and R. Sinha. 2018. How Disclosure Medium Affects Investor Reactions to CEO Bragging, Modesty, and Humblebragging. *Accounting, Organizations and Society,* 68-69: 118–134.

Green, T. C., R. Jame. And B. Lock. 2019. Executive Extraversion: Career and Firm Outcomes. *The Accounting Review* 94 (3): 177–204.

Hope, O.K., D. Hu, and H. Lu. 2016. The Benefits of Specific Risk-Factor Disclosures. *Review of Accounting Studies* 21 (4): 1005–1045.

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

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

Jung, M. J., J. P. Naughton, A. Tahoun, and C. Wang. 2018. Do Firms Strategically Disseminate? Evidence from Corporate Use of Social Media. *Accounting Review* 93 (4): 225–252.

Kim, I., and D. J. Skinner. 2012. Measuring securities litigation risk. *Journal of Accounting and Economics* 53 (1-2): 290–310.

Lee, L. F., A. P. Hutton, and S. Shu. 2015. The Role of Social Media in the Capital Market: Evidence from Consumer Product Recalls. *Journal of Accounting Research* 53 (2): 367–404.

Lin, K.Y., and H.P. Lu. 2011. Why People Use Social Networking Sites: An Empirical Study Integrating Network Externalities and Motivation Theory. *Computers in Human Behavior* 27 (3): 1152–1161.

Mao, Y., W. Wei, B. Wang, and B. Liu. 2012. Correlating S&P 500 Stocks with Twitter Data. In *Proceedings of the First ACM International Workshop on Hot Topics on Interdisciplinary Social Networks Research*: 69–72.

Mairesse, F. M. A. Walker, M. R. Mehl, and R. K. Moore. 2007. Using linguistic cues for the automatic recognition of personality in conversation and text. *Journal of Artificial Intelligence Research* 30: 457–500.

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

Pennington, J., R. Socher, and C. Manning. 2014. Glove: Global Vectors for Word Representation. In *Proceedings of the 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. August 28. Available at: https://www.pewresearch.org/fact-tank/2015/08/28/men-catch-up-with-women-on-overall-social-media-use/.

Pew Research Center. 2018. Social Media Use 2018: Demographics and Statistics. March 1. Available at: https://www.pewinternet.org/2018/03/01/social-media-use-in-2018/.

Sprenger, T. O., A. Tumasjan, P. G. Sandner, and I. M. Welpe. 2014. Tweets and Trades: The Information Content of Stock Microblogs. *European Financial Management* 20 (5): 926–957.

Tetlock, P. C. 2011. All the News That's Fit to Reprint: Do Investors React to Stale Information? *The Review of Financial Studies* 24 (5): 1481–1512.

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

Securities and Exchange Commission (SEC). 2008. Commission Guidance on the Use of Company Web Sites. Release Nos. 34-58288, IC-28351. Washington D.C.: SEC.

———. 2013. Report of Investigation Pursuant to Section 21(a) of the Securities Exchange Act of 1934: Netflix, Inc., and Reed Hastings. Release No. 69279. Washington D.C.: SEC.

Zhao, W. X., J. Jiang, J. Weng, J. He, E. P. Lim, H. Yan, and X. Li. 2011. Comparing Twitter and Traditional Media Using Topic Models. In *Advances in Information Retrieval*.

Appendix A. Variable Definitions

Variable	**Definition**
Dependent variables	
Exec on Twitter	An indicator for if the executive has both opened a Twitter account and posted his/her first tweet by the given date
Exec topic tweets	The number of tweets of a given topic (*financial*, *non-financial business*, or *non-business*) posted on the given day (daily tests) by the executive (CEO or CFO)
$MMRet_{window}$	Market model return, 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)
Independent variables	
10-K and 10-Q filing	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 event	An indicator for if the firm released an earnings announcement (annual or quarterly) on the given trading day (I/B/E/S) or conducted an earnings conference call on the given trading day (Capital IQ)
Exec topic tweets	The number of tweets of a given topic (*financial*, *non-financial business*, or *non-business*) posted on the given day (daily tests) by the executive (CEO or CFO)
Legal 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
News articles	The number of unique news articles in Dow Jones owned publications released about the firm on a given trading day using intraday data from Ravenpack Dow Jones Edition (filtering for at least 75% relevance and a unique *RP_STORY_ID*)
Post SEC	1 if the date is at or later than April 2, 2013, else 0
Press Releases	The number of unique press releases released by the firm on a given trading day using intraday data from Ravenpack PR Edition (filtering for at least 75% relevance and a unique *RP_STORY_ID*)
Tweet Similarity	The similarity of tweets by an executive to those by the firm in the 7 days preceding the tweet up until the second before the executive's tweet, averaged across the trading day. Distance is measured as the minimum Euclidean distance (L2 norm) between the USE vector representing the executive's tweet and the USE vectors representing

	the executive's firm's tweets. Similarity is given by (1 – Distance / 2) and is thus scaled to the range of [0,1], where 1 is most similar.
Control variables (executive)	
Executive age	Age of the CEO, in years (Execucomp)
Female	Indicator for if the executive is female (Execucomp)
Extraversion	Extraversion measured following Green, Jame and Lock (2019) using Street Events conference call transcript Q&As from January 10, 2001 through April 25, 2019
CEO	Indicator for if the executive is the CEO of the company (Execucomp)
CFO	Indicator for if the executive is the CFO of the company (Execucomp)
Control variables (event indicators)	
Business event	Indicator for if there was an 8-K or press release filed by the firm, or if there was a news article about the firm, on a given day
Financial event	Indicator for if the firm had an earnings announcement, conference call, 10-K filing released, or 10-Q filing released on a given day
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%
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*, these control variables are generally backfilled due to the point-in-time nature of the data. Firm data is first available as of January 2017, CEO data is first available as of January 2017, and CFO data is first available as of June 2017. For days missing these measures after the first date of availability, the most recent, previous, non-missing observation is used.
Firm on Twitter	An indicator for if the firm associated with the executive is both on Twitter and has tweeted at least once by the given date

Firm topic tweets	The number of tweets of a given topic (*financial*, *non-financial business*, or *non-business*) posted on the given day (daily tests) or quarter (quarterly tests) by the firm
log(Followers$_{Entity}$)	The log of one plus the number of Twitter accounts following the entity (firm or executive) on Twitter
log(Following$_{Entity}$)	The log of one plus the number of Twitter accounts that the entity (firm or executive) is following on Twitter
log(Total tweets$_{Entity}$)	The log of one plus the number of tweets that the entity has posted up to the given date

Fixed Effects	
Executive	The execid of the executive, as provided by Execucomp
Firm	The gvkey of the firm, as provided by Compustat Quarterly
Industry	The GIC Sector of the firm, as provided by Compustat Quarterly
Month	The month of the trading date: January, February, …
Year	The year of the trading date: 2011, 2012, …

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

Non-business

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

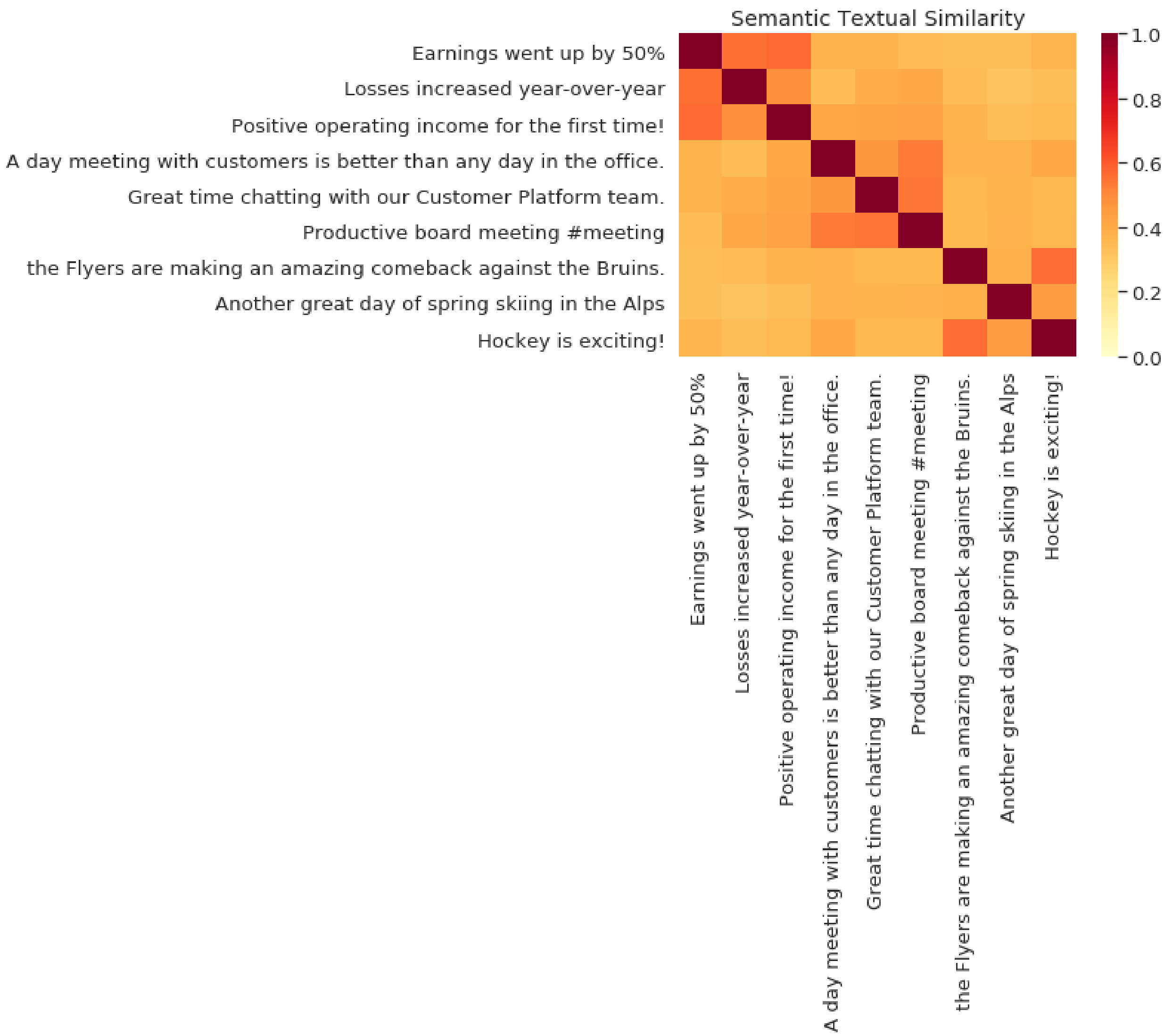
Appendix C. USE Method

Universal Sentence Encoder (USE) is an algorithm developed by Cer et al. (2018) for generating embeddings of sentences. An embedding is 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 accounting 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 pretrained DAN-based model provided on TensorFlow Hub.[23]

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 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 in order to convert to similarity.

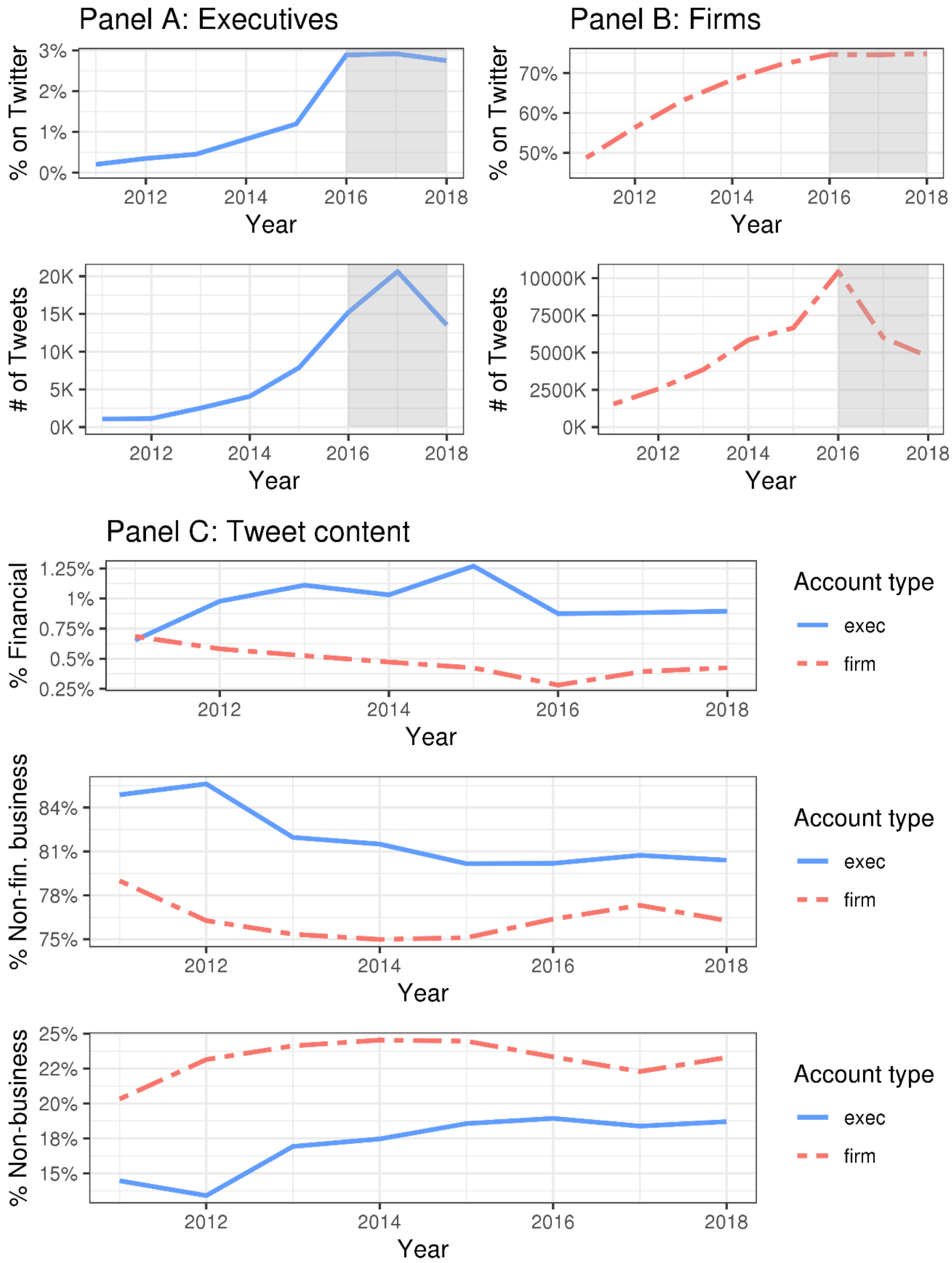
[23] The DAN based pretrained USE algorithm is available at: https://tfhub.dev/google/universal-sentence-encoder/2

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, non-business*) 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," as well as how it applies a slightly higher similarity to the tweets that are both positive (1 & 3) as compared to mixes of positive and negative (1 & 2), (3 & 2). For *non-financial business*, note how it understands that the third message is relatively abstract, and could sensibly link to the other two examples, yet the other two themselves, by being more specific, receive a relatively lower similarity. Lastly, for *non-business* 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: Twitter accounts and Tweets by year



Note: Panel A presents the percent of executives and number of tweets by executives on Twitter. Due to the sample construction methodology, data for 2017 and 2018 (in gray) may be understated.

Panel B presents the percent of S&P 1500 firms and number of tweets by those firms on Twitter. Due to the sample construction methodology, data for 2017 and 2018 (in gray) may be understated.

Panel C shows the average % of tweets categorized as *financial*, *non-financial business*, and *non-business* on Twitter across the sample, split by firm and executive.

Table 1: Univariate statistics, quarterly sample of all executives

Panel A: Univariate differences by executive Twitter account status

	Not on Twitter		On Twitter		On Twitter minus not on Twitter	
Variable	**Mean**	**S.D.**	**Mean**	**S.D.**	**Difference**	**t-stat**
Post SEC	0.739	0.439	0.886	0.319	0.147***	(6.69)
Legal risk	0.427	0.100	0.478	0.106	0.051***	(10.2)
Executive age	54.5	7.25	50.8	6.82	-3.71***	(-10.2)
Female	0.073	0.260	0.129	0.336	0.057***	(4.33)
Extraversion	3.90	0.542	3.99	0.581	0.082**	(3.01)
Time trend	4.03	1.46	4.71	1.24	0.685***	(9.36)
Size	8.26	1.72	8.10	1.99	-0.155	(-1.80)
ROA	0.010	0.028	0.009	0.035	-0.001	(-0.527)
MTB	1.29	1.29	1.75	1.47	0.456***	(7.08)
Debt	0.579	0.241	0.529	0.253	-0.050***	(-4.14)
Firm on Twitter	0.634	0.482	0.796	0.403	0.162***	(6.74)
log(Followers$_{Firm}$)	5.38	4.54	7.14	4.72	1.77***	(7.77)
log(Following$_{Firm}$)	3.83	3.33	5.13	3.51	1.30***	(7.80)
log(Total tweets$_{Firm}$)	4.68	3.87	6.08	3.97	1.39***	(7.19)
Observations	**56,203**		**402**			

Panel B: Executive Twitter account status by firm Twitter account status

	Exec not on Twitter	Exec on Twitter	Total
Firm not on Twitter	40.70%	0.13%	40.83%
Firm on Twitter	58.68%	0.48%	59.17%
Total	99.38%	0.62%	100%

Note: Panel A presents univariate statistics of the sample of quarter-executive-firm observations from 2011 through the end of 2016. The first two columns describe the means and standard deviations for the sample of quarter-executive-firm observations where the executive is not on Twitter, while the second two columns describe the means and standard deviations for the quarter-executive-firm observations where the executive was 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 (in parentheses). 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.

Table 2: Executives joining Twitter

VARIABLES	**Full sample, fiscal quarters**	
Post SEC	1.137	1.178
	(1.57)	(1.59)
Legal risk	5.579***	5.155***
	(4.18)	(3.78)
Legal risk x Post SEC	-2.247*	-2.355*
	(-1.65)	(-1.70)
Executive age		-0.076***
		(-9.89)
Female		0.456***
		(2.90)
Extraversion		0.239**
		(2.36)
Time trend	0.360***	0.379***
	(6.63)	(6.92)
Size	0.105**	0.098**
	(2.54)	(2.35)
ROA	-0.157	-0.077
	(-0.10)	(-0.05)
MTB	0.064*	0.059
	(1.79)	(1.59)
Debt	-0.230	-0.266
	(-0.99)	(-1.15)
Firm on Twitter	0.302	0.186
	(1.21)	(0.75)
log(Followers$_{Firm}$)	-0.006	-0.037
	(-0.14)	(-0.89)
log(Following$_{Firm}$)	0.137***	0.146***
	(3.14)	(3.22)
log(Total tweets$_{Firm}$)	-0.108*	-0.072
	(-1.73)	(-1.14)
Constant	-9.516***	-6.319***
	(-11.30)	(-6.54)
Industry FE	Yes	Yes
Pseudo R-sq	**0.0871**	**0.111**
Sample size	**47,492**	**47,492**

Note: This table presents the results of regression equation (1) on the fiscal quarter sample of executives using a logistic regression model. The sample used for these regressions is truncated such that all observations occur prior to 2017. 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

Variable	N	Mean	S.D.	p5	p50	p95
Exec financial tweets	70,828	0.009	0.112	0	0	0
Exec non-fin. business tweets	70,828	0.753	3.01	0	0	4
Exec non-business tweets	70,828	0.171	0.828	0	0	1
Firm financial tweets	70,828	0.059	0.376	0	0	0
Firm non-fin. business tweets	70,828	16.3	87.5	0	2	50
Firm non-business tweets	70,828	4.64	30.8	0	0	12
Executive age	70,828	52.5	6.89	41	52	63
Female	70,828	0.114	0.318	0	0	1
Extraversion	70,828	4.23	0.550	3.15	4.23	5.02
CEO	70,828	0.630	0.483	0	1	1
CFO	70,828	0.372	0.483	0	0	1
Size	70,828	8.76	2.01	5.29	8.85	11.8
ROA	70,828	0.008	0.035	-0.024	0.011	0.049
MTB	70,828	1.90	1.91	0.167	1.21	5.56
Debt	70,828	0.592	0.251	0.155	0.623	0.974
Firm on Twitter	70,828	0.854	0.353	0	1	1
$log(Followers_{Firm})$	70,828	8.58	4.56	0	9.75	14.6
$log(Following_{Firm})$	70,828	5.93	3.22	0	6.66	10.35
$log(Total\ tweets_{Firm})$	70,828	7.20	3.74	0	8.45	11.03
$log(Followers_{Exec})$	70,828	6.94	2.78	2.89	7.03	11.9
$log(Following_{Exec})$	70,828	4.83	1.46	2.40	5.08	6.96
$log(Total\ tweets_{Exec})$	70,828	5.31	1.90	1.95	5.37	8.12

Note: This table presents univariate statistics of the sample of trading day-executive-firm observations restricted to trading days where the executive had an active Twitter account with at least 1 tweet posted that day or prior.

Table 4: Executive response on Twitter to information events

Panel A: Executive tweets and earnings announcements/conference calls

VARIABLES	***Financial***	***Non-Fin. Business***	***Non-business***
Earnings Event	1.865***	0.051	-0.065
	(11.92)	(0.74)	(-0.55)
All Controls	Yes	Yes	Yes
Firm, Exec, year, & month FE	Yes	Yes	Yes
Pseudo R-sq	**0.190**	**0.533**	**0.442**

Panel B: Executive tweets and SEC filings

VARIABLES	***Financial***	***Non-Fin. Business***	***Non-business***
10-K and 10-Q filing	0.894***	0.081	0.086
	(3.79)	(0.88)	(0.75)
8-K filings	1.230***	0.188***	0.122**
	(10.29)	(4.28)	(2.14)
All Controls	Yes	Yes	Yes
Firm, Exec, year, & month FE	Yes	Yes	Yes
Pseudo R-sq	**0.199**	**0.533**	**0.442**

Panel C: Executive tweets and press releases

VARIABLES	***Financial***	***Non-Fin. Business***	***Non-business***
Press Releases	0.072***	0.036***	0.034***
	(8.53)	(9.60)	(7.54)
All Controls	Yes	Yes	Yes
Firm, Exec, year, & month FE	Yes	Yes	Yes
Pseudo R-sq	**0.185**	**0.535**	**0.443**

Panel D: Executive tweets and news articles

VARIABLES	***Financial***	***Non-Fin. Business***	***Non-business***
News articles	0.054***	0.012***	0.006***
	(9.39)	(8.89)	(3.56)
All Controls	Yes	Yes	Yes
Firm, Exec, year, & month FE	Yes	Yes	Yes
Pseudo R-sq	**0.202**	**0.534**	**0.442**

Note: This table presents the results of regression equation (2) on the daily sample of executives using a Poisson pseudo maximum likelihood (PPML) regression. The dependent variables are counts of the number of tweets posted by a manager on a given trading day. 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

	| MMR$_{(+1)}$ |		
VARIABLES	***Financial***	***Non-Fin. Business***	***Non-business***
Exec topic tweets	0.003***	-0.000	-0.000
	(2.99)	(-1.53)	(-1.06)
Firm topic tweets	0.000**	-0.000	0.000
	(2.57)	(-1.53)	(0.77)
$\|MMR_{(-1)}\|$	0.074***	0.074***	0.074***
	(6.79)	(6.80)	(6.79)
Financial event	0.015***	0.015***	0.015***
	(17.26)	(17.42)	(17.42)
Business event	0.001***	0.001***	0.001***
	(7.91)	(8.00)	(7.97)
Executive age	0.000	0.000	0.000
	(1.42)	(1.48)	(1.49)
Size	-0.001***	-0.001***	-0.001***
	(-3.81)	(-3.79)	(-3.78)
ROA	0.001	0.001	0.001
	(0.15)	(0.17)	(0.18)
MTB	-0.001***	-0.001***	-0.001***
	(-7.60)	(-7.58)	(-7.57)
Debt	0.001	0.001	0.001
	(0.88)	(0.88)	(0.89)
Firm on Twitter	-0.005***	-0.005***	-0.005***
	(-2.80)	(-2.88)	(-2.83)
log($Followers_{Firm}$)	0.001***	0.001***	0.001***
	(2.67)	(2.64)	(2.62)
log($Following_{Firm}$)	-0.000	-0.000	-0.000
	(-1.34)	(-1.15)	(-1.26)
log(Total $tweets_{Firm}$)	-0.001*	-0.001*	-0.001*
	(-1.74)	(-1.72)	(-1.69)
log($Followers_{Exec}$)	0.001	0.001	0.001
	(1.53)	(1.58)	(1.60)
log($Following_{Exec}$)	-0.000	-0.000	-0.000
	(-0.25)	(-0.05)	(-0.06)
log(Total $tweets_{Exec}$)	-0.003***	-0.003***	-0.003***
	(-5.03)	(-5.00)	(-5.02)
Constant	0.016	0.014	0.014
	(1.00)	(0.89)	(0.88)
Firm FE	Yes	Yes	Yes
Exec FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
Adj R-Sq	**0.134**	**0.134**	**0.134**
Observations	**70,440**	**70,440**	**70,440**

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+1. *Exec topic tweets* and *Firm topic tweets* capture counts of different tweet types for each column: *financial* tweets, *non-financial business* tweets and *non-business* tweets in the first, second and third column, respectively. *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: Horizon of market response to financial tweets

VARIABLES	**| MMR$_{(0)}$ |**	**| MMR$_{(+1)}$ |**	**| MMR$_{(+2)}$ |**	**| MMR$_{(+3)}$ |**	**| MMR$_{(+4)}$ |**	**| MMR$_{(+5)}$ |**
Exec financial tweets	0.001	0.003***	-0.000	0.001*	-0.000	-0.000
	(1.18)	(2.99)	(-0.34)	(1.67)	(-1.17)	(-0.01)
Firm financial tweets	-0.000**	0.000**	0.000	0.000	0.000	0.000
	(-2.05)	(2.57)	(0.64)	(0.57)	(0.84)	(0.71)
|MMR$_{(-1)}$|	0.140***	0.074***	0.051***	0.041***	0.039***	0.038***
	(5.65)	(6.79)	(9.62)	(7.69)	(7.58)	(7.39)
Financial event	0.022***	0.015***	0.002***	0.000	-0.000	-0.001***
	(21.49)	(17.26)	(6.63)	(0.60)	(-0.94)	(-3.45)
Business event	0.003***	0.001***	-0.000	-0.000	-0.000*	-0.000*
	(16.80)	(7.91)	(-1.24)	(-0.05)	(-1.75)	(-1.77)
Executive age	0.000	0.000	0.001**	0.001***	0.001***	0.000
	(0.69)	(1.42)	(2.35)	(2.61)	(2.70)	(1.20)
Size	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(-4.06)	(-3.81)	(-3.50)	(-3.55)	(-3.42)	(-3.30)
ROA	0.001	0.001	0.000	-0.000	-0.001	-0.001
	(0.18)	(0.15)	(0.01)	(-0.03)	(-0.21)	(-0.19)
MTB	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(-7.09)	(-7.60)	(-7.40)	(-7.46)	(-7.35)	(-7.33)
Debt	0.001	0.001	0.001	0.001	0.002	0.001
	(0.74)	(0.88)	(0.87)	(0.96)	(1.06)	(1.05)
Firm on Twitter	-0.004***	-0.005***	-0.006***	-0.006***	-0.006***	-0.005***
	(-2.61)	(-2.80)	(-3.19)	(-3.31)	(-3.21)	(-3.01)
log(Followers$_{Firm}$)	0.001**	0.001***	0.001***	0.001***	0.001***	0.001***
	(2.42)	(2.67)	(2.94)	(3.12)	(3.02)	(2.85)
log(Following$_{Firm}$)	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(-1.40)	(-1.34)	(-1.11)	(-1.21)	(-1.11)	(-1.31)
log(Total tweets$_{Firm}$)	-0.001	-0.001*	-0.001**	-0.001**	-0.001**	-0.001*
	(-1.62)	(-1.74)	(-2.08)	(-2.11)	(-2.10)	(-1.83)
log(Followers$_{Exec}$)	0.001	0.001	0.001	0.001	0.001	0.001
	(1.23)	(1.53)	(1.53)	(1.51)	(1.54)	(1.59)
log(Following$_{Exec}$)	-0.000	-0.000	-0.000	-0.000	-0.000	0.000
	(-0.11)	(-0.25)	(-0.15)	(-0.19)	(-0.12)	(0.10)
log(Total tweets$_{Exec}$)	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.004***
	(-4.47)	(-5.03)	(-5.06)	(-5.04)	(-5.07)	(-5.15)
Constant	0.025	0.016	0.002	-0.002	-0.004	0.014
	(1.62)	(1.00)	(0.12)	(-0.11)	(-0.24)	(0.67)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Exec FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj R-Sq	**0.177**	**0.134**	**0.110**	**0.108**	**0.109**	**0.109**
Observations	**70,494**	**70,440**	**70,274**	**70,164**	**70,054**	**69,944**

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 ranges from absolute market model return on day t through absolute market model return on day t+5 in increments of 1 day. *Exec financial tweets* and *Firm financial tweets* capture counts of financial tweets for executives and firms, respectively. *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: Content or trust

VARIABLE	$\lvert MMR_{(+1)} \rvert$	t-value
Exec topic tweets	-0.015	(-1.57)
Tweet similarity x Exec financial tweets	0.038*	(1.91)
Firm topic tweets	-0.006***	(-2.78)
Tweet similarity x Firm financial tweets	0.006***	(3.00)
$\lvert MMR_{(-1)} \rvert$	0.074***	(6.74)
Financial event	0.015***	(17.18)
Business event	0.001***	(8.01)
Executive age	0.000	(1.42)
Size	-0.001***	(-3.85)
ROA	0.000	(0.11)
MTB	-0.001***	(-7.64)
Debt	0.001	(0.83)
Firm on Twitter	-0.005***	(-2.82)
$log(Followers_{Firm})$	0.001***	(2.59)
$log(Following_{Firm})$	-0.000	(-1.18)
$log(Total\ tweets_{Firm})$	-0.001*	(-1.73)
$log(Followers_{Exec})$	0.001	(1.51)
$log(Following_{Exec})$	-0.000	(-0.40)
$log(Total\ tweets_{Exec})$	-0.003***	(-5.00)
Constant	0.016	(1.03)
Firm, Exec, Year, & Month FEs	Yes	
Adj R-Sq	**0.135**	
Observations	**70,214**	

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) while including an interaction between tweeting behavior and *tweet similarity*. *Tweet similarity* is the similarity between the executive's financial tweets on a given day and the firm's tweets in the 7 days directly preceding the tweet (up to the second before the executive's tweet). The dependent variable is absolute market model return on day t+1. The 226 observations where *Tweet similarity* is undefined due to having no firm tweets matching an executive's tweet are dropped from the sample. *Exec financial tweets* and *Firm financial tweets* capture counts of financial tweets for executives and firms, respectively. *t* statistics are presented in parentheses in column 3, and significance is denoted as follows: *** denotes $p < 0.01$, ** denotes $p < 0.05$, and * denotes $p < 0.10$.