Discretionary Disclosure on Twitter

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Abstract

Using a machine learning approach to process 12.8 million tweets from S&P 1500 firms posted from 2012 to 2016, we find that firms selectively disclose corporate events on Twitter and choose to post financial disclosures on Twitter more frequently around earnings announcements, accounting filings, and firm-specific news events. Financial disclosures on Twitter are also more likely to contain media (image or video) and links around these events. Our large-sample evidence suggests that firms are more likely to disseminate news on Twitter when it is significantly good or bad. Finally, we find that firms with limited attention are more likely to exercise discretion and that feedback from Twitter users encourages future financial tweets and use of media and links. These findings suggest that firms make use of discretionary disclosure on Twitter and that the unique feedback mechanism on Twitter has affected information dissemination in a dynamic manner.

Keywords: Social media; discretionary disclosure; dissemination; Twitter; limited attention; feedback.

JEL Codes: G14; L30; M14; M15; M40

Discretionary Disclosures on Twitter

1. Introduction

Over the past decade, social media, such as Twitter, has dynamically transformed the way in which information about firms is produced, disseminated, and processed. Research has found that firms can reduce information asymmetry by disseminating their news via social media (Blankespoor, Miller, and White, 2014; Lee, Hutton, and Shu, 2015; Jung, Naughton, Tahoun, and Wang, 2017) and that textual content on Twitter can help predict overall stock market or firm performance (Sprenger, Tumasjan, Sander, and Welpe, 2013; Bartov, Faurel, and Mohanram, 2017; Tang, 2017). Firms can choose strategically which information events to disclose on social media and what format to use (plain text versus formatting tweets using hyperlinks or media attachments). Therefore, investors can acquire additional information on company-related issues by reading tweets generated by those companies, and the firms in turn can learn about investors' preferences from the feedback they provide instantaneously (e.g., likes, retweets, and replies). The ultimate disclosure pattern is the equilibrium choice of dynamic play between investors and firms.

Beginning from the premise that 'we shape our tools, and thereafter our tools shape us', Marshall McLuhan, the father of communications and media studies, suggested that content follows form, and that insurgent technologies give rise to new structures of feeling and thought. In his influential book Understanding Media, he coined the expression 'the medium is the message' (McLuhan, 1964). The main idea behind McLuhan's theory is that the way in which a message is relayed—the medium—influences how it is perceived. McLuhan applied his theory to media including telephone, radio, and television, and conceived the concepts of the information age and the global village 50 years ago. His theory helps explain why we communicate through more than

one medium, even if the message is the same. Motivated both by McLuhan's media theory in communication research and disclosure theory in accounting research, we assume that managers (information senders) anticipate that investors (information recipients) will respond in different ways depending on the medium, even if the same information is presented. The purpose of our study is thus to explore the types of events, timing, and format of corporate disclosure on Twitter.

As a new medium of communication, Twitter is unique—it has a strict character limit for each tweet, so the message must be simple, short, concise, and tangible. Firms can bypass the limit by including multimedia such as hyperlinks or media attachments (images and videos), giving receivers the option to read further. Twitter enables firms to initiate direct communication with a network of followers. It also enables followers to 'like' a tweet with a simple click. Using the like feature on Twitter, followers can express positive sentiment regarding tweets. Followers can also spread the message by retweeting to their followers. As the size of the followers' network increases, so does the firm's potential to reach and influence a wider audience. According to data analyzed by Statista, by 2015 over 80% of Twitter users were accessing their accounts via mobile devices,[1] and this percentage continues to grow. In contrast to a pull information system, where the request for the transmission of information is initiated by the recipient, the push technology of social media significantly reduces the search and processing costs for information recipients and increases speed of communication. More importantly, by monitoring investors' reactions to firm disclosures continuously via the functions of likes, retweets, replies, etc., firms can adjust their choices of events, timing, and format dynamically in their disclosures.

Using a sample of 12.8 million tweets posted by 1,215 S&P 1500 companies with active Twitter accounts from 2012 to 2016, we test three hypotheses. The first two investigated how

[1] See https://www.statista.com/chart/1520/number-of-monthly-active-twitter-users/.

tweeting activity is associated with earnings announcements, accounting filings, and other concurrent news events. We began the tests by evaluating companies' tweeting activity on three dimensions: (1) the content of tweets (financial); (2) the timing of tweets around corporate news events; and (3) the format of tweets. Throughout this paper, we refer to tweets that contain hyperlinks or media attachments as 'tweets with formatting' (or 'formatted tweets') as opposed to tweets with plain text only. Our third hypothesis examines how investor attention affects the above discretionary tweeting activities. We use institutional ownership and the feedback from Twitter's users around previous disclosures to proxy for investor attention.

Because Twitter is an additional medium of communication, we argue that firms/managers will tweet more to exert their influence on Twitter if and only if they anticipate that information already disclosed elsewhere (typically through conventional channels like SEC filings, press releases, or conference calls) has a significantly positive or negative outcome. If existing information reflects a neutral outcome, however, investors will present less demand for the information, and firms/managers will have less incentive to tweet. Following this line of reasoning, we predict that firms choose the timing of communications to coincide with their earnings announcements and accounting filings, and that they selectively disclose corporate events with a clear news direction (i.e., positive or negative) on Twitter. Test results show that firms increase tweeting and specifically financial tweets around earnings announcements as well as quarterly and annual report filings. A similar tweeting pattern is observed around announcements of mergers and acquisitions (M&A), financial news, management forecasts, and executive information. As predicted, we also find that companies tweet more financial news around these news events whenever the events are significantly negative or positive. Furthermore, we find that firms are more likely to post a formatted tweet (i.e., tweets containing media or a link), around earnings

announcements, accounting filings, and news on M&A, financials, management forecasts, and executives. Firms are also more likely to use formatting around news events with a clear positive or negative direction, and are less likely to do so around neutral news. Collectively, the evidence suggests that firms selectively choose the timing and format of their tweets.

We then test whether the discretionary choice of timing and the format of tweets is conditional upon investor attention. Prior research suggests that information is incorporated into price gradually as news diffuses across the market (Hong and Stein, 1999) and that investors sometimes neglect relevant aspects of the information that is publicly disclosed due to limited attention and resources in processing information (Merton, 1987; Hirshleifer and Toeh, 2003). Twitter rapidly gained popularity for company communication and investor relations (IR). Thus, we predict that firms with less investor attention have a higher propensity to communicate financial information to their Twitter followers to attract attention. We first use institutional ownership to proxy for investor attention. To the extent that institutional investors have more resources and closer contacts with corporate management, they are more likely to gain firm-specific information via traditional channels such as public earnings conference calls, press releases, or private phone calls. Hence, social media is a less important avenue of communication for institutional investors than for naïve investors.[2] Consistent with our conjecture, we find that both tweet timing and format differ between the two groups: firms with lower institutional ownership are more likely to tweet around earnings announcements. Among financial tweets, firms with lower institutional ownership are more like to use formatting around earnings announcements than firms with higher institutional

[2] Brown et al. (2017a) surveyed 610 investor relations officers (IROs) of US public firms, of whom they asked the following question: 'How important are the following for conveying your company's message to institutional investors?' Relative to other channels, such as conference calls, press releases, private phone calls, only 2% of respondents stated that social media was 'very important', while 66% considered it 'not important'. Not surprisingly, public earnings conference calls are still rated the most important venue for management to convey their companies' message to institutional investors.

ownership. We also found that the pattern of tweeting more financial news around significantly negative or positive news events is stronger among the firms with lower institutional ownership. Finally, we use feedback indicators (i.e., whether a financial tweet received likes, retweets, or replies) as an alternative proxy for investor attention and find that feedback from Twitter users affects firms' future tweeting behavior, encouraging more financial tweets and use of formatting for financial tweets.[3]

Our paper makes several significant contributions to the literature. First, it extends recent research on corporate use of social media by examining firms' tweeting activity around a comprehensive set of accounting and corporate news events. Our study is the first to use machine learning algorithms to classify a large volume of tweets (12.8 million) into financial and non-financial tweets. This approach offers a more bias-free assessment of the content of the examined tweets and improves classification precision over a dictionary approach. We highlight that firms strategically select the types of event and timing to disseminate financial information on Twitter to reach more investors.[4] Moreover, we present evidence that tweeting format is not a random choice and that it varies with both the type of news event and the direction of the news. Unlike existing studies, which focus on the effect of tweet content to show firms' opportunistic use of social media (e.g., Lee et al., 2015; Jung et al., 2017), our study examines firms' choice of tweeting events, timing, and format. Our findings add a new dimension to the understanding of how firms

[3] This is consistent with anecdotal evidence. Brown et al. (2017a) reported that one IRO commented on how he used social media in his role: 'We're not active contributors, but we're active consumers of social media because Twitter is the medium of choice for market structure and day trading conversations … Twitter helps you identify things that people care about'.

[4] Some studies use the word 'dissemination' specifically for information disclosed elsewhere (e.g., Jung et al., 2017). Since firms directly disseminate information to their Twitter followers, such information often overlaps with that disclosed on company websites or the SEC's EDGAR website, or highlights information which may not appear in their financial statements. Thus, for many investors, particularly retail investors, the content they read on companies' social media outlets is still new information.

use Twitter and its embedded functions effectively to manage information flow to the capital market.

Second, we provide large-sample empirical evidence showing firms' strategic dissemination behavior and highlight the effect of feedback on disclosure. It is commonly believed that managers have incentives to disclose bad news voluntarily due to capital market pressure and litigation risk. This perception is drawn from theoretical analysis, empirical work, and field studies (e.g., Verrecchia, 1983; Dye, 1985; Skinner, 1994; Graham, Harvey, and Rajgopal, 2003). However, strategic dissemination on social media is new. Jung et al. (2017) find that firms are less likely to disseminate news on Twitter when the news is bad and when the magnitude of the bad news is worse. However, in contrast, our evidence shows that firms are equally likely to disseminate good and bad news on Twitter and that the pattern is independent of the likelihood of litigation. Importantly, since Twitter allows investors to provide immediate feedback on tweets through likes, retweeting, or replying, we show that firms learn from feedback and adjust their disclosure behavior accordingly. This new evidence suggests that the equilibrium of information dissemination is dynamic.

Finally, our study has policy implications. The Securities and Exchange Commission (SEC) issued guidance in April 2013 permitting firms to use social media platforms to release company-related information in compliance with Regulation Fair Disclosure (Reg FD). According to the SEC, 'We appreciate the value and prevalence of social media channels in contemporary market communications, and the Commission supports companies seeking new ways to communicate and engage with shareholders and the market' (SEC, 2013). Nevertheless, corporate disclosure on social media is primarily voluntary and for the most part unregulated. Our study provides evidence that the new disclosure channel of Twitter seems to be effective in attracting attention from retail

investors. These findings provide useful insights for regulators and users of financial information on how firms manage information flow to the capital market.

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

2. Literature Review and Hypothesis Development

2.1 Literature review

The notions that managers have incentives to engage in discretionary disclosure and that corporate disclosure has economic consequences are well established in the literature (e.g., Verrecchia, 1983; Dye, 1985; Fields, Lys, and Vincent, 2001; Healy and Palepu, 2001; Beyer, Cohen, Lys, and Walther, 2010; Leuz and Wysocki, 2016). Strategic disclosure behavior has been documented in various settings. For example, a number of studies on conference calls examine management's strategic communication and its association with information content (Hollander, Pronk, Roelofsen, 2010), firm performance (Mayew and Venkatachalam, 2012), financial fraud, and misreporting (Hobson, Mayew, and Venkatachalam, 2012; Larcker and Zakolyukina, 2012). Some other studies examining the role of newswires in the capital market find that the business press reduces information asymmetry (Bushee, Core, Guay, and Hamm, 2010) and that increased newswire dissemination of management earnings guidance facilitates price discovery (Twedt, 2016). Collectively, research on corporate disclosure largely focuses on conventional channels of disclosure.

Recently, the academic literature has started to study the role that social media, such as Twitter, plays in the capital market. One strand of the literature examines corporate use of Twitter and other social media outlets. For example, Blankespoor et al. (2014) use a sample of 85 technology firms and find that firms can reduce information asymmetry by using Twitter to

disseminate their news. Lee et al. (2015) examine how corporate social media affects the capital market consequences of firms' disclosure in the context of consumer product recalls, and find that corporate social media attenuates the negative price reaction to recall announcements. Miller and Skinner (2015) discuss Lee et al. (2015) and four other papers on the role of disclosure in financial markets, and provide a framework identifying several important themes in the disclosure literature, encouraging future research to continue exploring emerging forces in disclosure, such as the role of social media.

Another strand of the literature focuses on content analysis of tweets and investigates whether the messages posted on corporate Twitter accounts can help predict future firm-level performance and/or the stock market as a whole. This research theme stems from the information systems field. For example, Bollen, Mao, and Zheng (2011) show that aggregate investor mood inferred from the textual analysis of daily Twitter feeds can help predict changes in the Dow Jones index. Similarly, Mao, Wei, Wang, and Liu (2012) find that the daily number of tweets that mention S&P 500 stocks is significantly correlated with S&P 500 levels, changes, and absolute changes. Using approximately 250,000 stock-related tweets, Sprenger et al. (2013) demonstrate a significant association between Twitter message features (i.e., sentiment, volume, and disagreement) and market features (i.e., stock returns, trading volume, and volatility). Curtis, Richardson, and Schmardebeck (2014) investigate whether investor activity on Twitter can influence investor response to earnings news. They find that high levels of investors' Twitter activity are associated with greater sensitivity of earnings announcement returns to earnings surprises (higher beta in the returns/earnings regression), while low levels of Twitter activity are associated with significant post-earnings-announcement drift. More recently, Bartov et al. (2017)

and Tang (2017) find that information contained in tweets can help predict firm-level future earnings, sales, and stock returns.

Although there is early evidence that firms are increasingly using Twitter to disseminate company-related information, there is little evidence on how firms might make discretionary choices in selecting certain events, timing, and formatting to disclose news on Twitter. Jung et al. (2017) study firms' decision to disseminate quarterly earnings news through social media and conclude that firms are less likely to disseminate earnings news through social media when the news is negative, and that the pattern is stronger among firms with high litigation risk. Their evidence suggests that firms are opportunistic in disseminating information on social media, which bears a similarity to their strategic disclosure behavior through other channels. Huang, Lu, and Su (2017) document that firms ranked as having high environmental performance by Newsweek magazine post more tweets on their green activities. Such disclosures attract more individual investors and thus increase both stock liquidity and return volatility.

Our study adds to the literature by focusing on the timing and format of company tweets in connection with significant corporate events and by showing how the decision to disseminate information on social media varies with investor attention and the feedback from Twitter followers. Ours is the first study to use machine learning algorithms to process a large volume of tweets (12.8 million) in order to study financial disclosure on social media. It thus provides a unique perspective on corporate use of social media as an innovative disclosure channel with instantaneous and continuous feedback.

2.2 Hypotheses development

Twitter is a quick means to convey information to investors. Firms can bypass the 140-character constraint by embedding hyperlinks or media attachments such as images and videos.

Twitter allows firms to initiate communication with followers directly; this feature significantly reduces communication and investor search costs compared to disseminating information through traditional channels. Twitter also allows firms to monitor investors' immediate reactions to tweets via features such as likes, retweets, and replies, so that they can revise their disclosure strategies accordingly. While we do not expect investors to replace reading press releases and quarterly/annual reports with reading tweets, it is reasonable to believe that Twitter is an effective and efficient vehicle to bring investors' attention to unscheduled events and that investors may gather different perspectives on firms when they receive supplemental information on Twitter. To the extent that Twitter can alter investors' access to information and therefore the distribution of information, we argue that both firms and investors will give more weight to information disclosed via both Twitter and traditional channels than those disclosed only via traditional channels.

Naturally, firms should make discretionary choices when choosing which events to disclose on Twitter. Tweeting offers firms the opportunity to achieve a number of different objectives, for example, highlighting more important news events, promoting the company and new products, creating a positive social image, maintaining a transparent information environment, and attracting more followers.[5] Therefore, we expect firms to be proactive in disclosing events over which they have full control. Classifying exogenous information events into corporate events (M&A, earnings announcements, management forecasts, executive announcements), corporate insider-related events (insider trading), and external events (such as analyst forecasts and recommendations on firms), we expect firms to increase their use of tweets only for corporate

[5] The marketing literature has documented users' motivations to contribute content to Twitter and shown that social media can be used to generate growth in sales, return on investment, and positive word of mouth (e.g., Kumar, Bhaskaran, Mirchandani, and Shah, 2013; Toubia and Stephen, 2013).

events and around important events, such as when they announce earnings or file 10-K, 10-Q, and 8-K filings with the SEC.

While the literature on voluntary disclosure in general suggests that firms disclose differently depending on the direction of the information available to the capital market, the evidence on how firms disclose positive and negative news is mixed. Different assumptions and settings in theoretical models may lead to different predictions. On the assumption that managers maximize stock prices, Verrecchia (1983) shows that firms have disclosure thresholds due to propriety information while Dye (1985) argues that these thresholds exist even when there is no propriety information. Assuming that managers' incentives are aligned with those of investors, for example, avoiding over- or under-valuation, Hummel, Morgan, and Stocken (2017) develop a general model of persuasion games in which they show that managers will disclose extreme news and withhold moderate news if their interests and those of investors are more or less aligned. Empirical studies show mixed evidence and discuss various incentives. Managers have incentives to make timely disclosure of good news to maximize firm value while managers also have incentives to disclose bad news to deter competition or mitigate litigation risk (e.g., Skinner, 1994; Kasznik and Lev, 1995; Enache, Li, and Riedl, 2017). While information disclosed on Twitter is not necessarily completely new, we conjecture that the incentives for disclosure and dissemination largely overlap. Building on these theoretical and empirical arguments from the voluntary disclosure literature, we expect financial tweets in connection with significant news to increase and any change of tweeting behavior after neutral news to be minimal. The first set of hypotheses are thus as follows:

Hypothesis 1a: Firms choose the timing of financial disclosures on Twitter to coincide with their earnings announcements and SEC filings.

Hypothesis 1b: Firms selectively disclose on Twitter around corporate events with a clear news direction (positive or negative).

The purpose of testing this set of hypotheses is to provide descriptive evidence on companies' likelihood of tweeting financial information and the timing of company tweets in relation to earnings announcements and SEC filing dates (10-K, 10-Q, and 8-K). As will be discussed in subsection 3.2, we use a machine learning algorithm to examine the content of each company-generated tweet and to classify it in one of the following categories: business, marketing, and other tweets. Business related tweets are further classified into financial and non-financial (i.e., other business) tweet categories. We hand-classify events in RavenPack as positive, negative, and neutral based on RavenPack's news event taxonomy. Alternatively, we also compute the cumulative abnormal returns in the three-day event window, CAR (-1, +1), and classify returns as positive (negative) if the three-day CAR is 1.645 standard deviations above (below) zero (i.e., if the returns are outside a 90% confidence interval).

If managers exercise discretion in timing their Twitter disclosures and intensify their tweet activities in certain periods, they may also explore ways to disseminate more information in each tweet. One way to increase the capacity of tweets is to include links and/or media. The inclusion of hyperlinks and media can point tweet receivers to other, more comprehensive information sources or media which either contain further information or highlight key information. We thus present our second set of hypotheses:

Hypothesis 2a: Firms choose disclosure format (whether tweets are plain text or formatted) on Twitter in connection with news events.

Hypothesis 2b: Firms make more use of disclosure format (whether tweets are plain text or formatted) on Twitter when news events have a clear direction (positive or negative).

Blankespoor et al. (2014) attempt to isolate the impact of news dissemination by limiting their sample to company tweets containing hyperlinks to firm-initiated press releases. However, no academic research has examined the circumstance under which companies are more likely to embed formatting elements such as links, images, or videos into their tweets. We conjecture that investors perceive the choice of format to be reflective of the weight which firms give to events. Similar to our prediction on tweet timing, we expect firms to be more likely to use formatting in financial tweets to enhance the disclosure whenever the news has a clear direction (positive or negative) and less likely to do so when the news has a neutral outcome.

Our third hypothesis investigates the relationship between investor attention and the choice of timing and formatting in company tweets. Twitter utilizes a 'push' approach, allowing senders to initiate the transmission of information directly to followers rather than requiring the latter to request it. As noted earlier, over 80% of Twitter users access their accounts via mobile devices. Twitter thus bypasses information intermediaries and serves as a free channel that makes information much easier to access and allows firms to reach a broader audience quickly. This particularly benefits retail investors, who have few of the resources or skills needed to search for information about firm fundamentals or the stock market in the traditional 'pull' information system. At the firm level, research suggests that the traditional press is biased toward coverage of highly visible firms, because there is high demand for such news (Miller, 2006). Therefore, we expect the use of Twitter as a new alternative dissemination channel for information to be more beneficial to firms that are less visible and have fewer communication channels. Compared to plain text messages, tweets with hyperlinks directing users to company websites or existing press releases not only appear to be more credible but also allow companies to convey more information than can be included within a 140-character tweet. Regarding media attachments, a picture is worth

a thousand words. This means that embedding media elements such as images and videos will make a tweet more engaging and increase the amount of attention senders (firms) get. Following this intuition, we state the third hypothesis as follows:

Hypothesis 3: Firms with limited attention from investors are more likely to choose timing and formatting to coincide with news events when disclosing financial information.

We use institutional ownership and feedback from Twitter users around previous disclosures to proxy for investor attention. Institutions are professional investors; they are more likely to pay attention to big news events regarding the firms in which they invest. Low institutional ownership implies a relatively high percentage of retail investors and low investor attention. Feedback from Twitter users is the outcome of attention. We assume that tweets would generate strong feedback for firms with limited attention because investors in these firms find information disseminated via Twitter to be more useful. In other words, feedback and attention should be negatively correlated after controlling for the number of followers. We test this hypothesis by examining variance of tweet timing and format around news events with attention proxies. While we do not have a clear prediction for each specific event, in general, we expect firms to use Twitter to draw investors' attention around highly visible accounting events like quarterly earnings announcements. Our intuition is that earnings announcements are of first-order importance to retail investors, and that earnings are among the most common topics of business tweets. While sophisticated investors likely obtain earnings information elsewhere—from press releases, conference calls, analysts, or SEC filings—firms can use Twitter to disseminate earnings information quickly and reach more naïve investors. Firms can also include hyperlinks to direct investors to read earnings reports on their websites, or use images and videos to highlight key statistics of their financial performance. Therefore, we expect firms with a low level of attention

from investors to tweet more and to make more use of formatting features around financial news than firms already receiving a high level of attention from investors.

3. Data and methodology

3.1 Data and sample selection

Our sample consists of all public firms that were contained in the S&P 1500 at any point between January 1, 2012 and September 30, 2016, and our analysis covers all tweets posted by these firms from January 1, 2012 through December 31, 2016. We hand-collect the Twitter handles of all these firms and, based on these, identify Twitter IDs via Twitter API 2.0 associated with each account. While Twitter handles can be changed (for instance, after mergers or rebranding), Twitter IDs are a permanent identifier, allowing us to track companies across multiple Twitter handles. In total, we identified 1,443 Twitter accounts. Among S&P 1500 firms in our sample period, 383 firms have no Twitter accounts, 590 firms adopt Twitter during our sample period, and 853 firms have an account throughout. After removing accounts that are protected (i.e., that make their tweets only available to followers) and accounts that have never tweeted, our data set contains 1,215 companies' Twitter accounts, of which 440 have adopted Twitter during the sample period and 775 have an account throughout.

To obtain companies' tweets, we used Twitter API 2.0 to download all publicly available tweets associated with each Twitter ID. Public access is limited to the 3,200 most recent tweets per account. There were 614 accounts which posted more than 3,200 tweets over our sample period; in these cases, we purchased a complete set of tweets for each company from GNIP, one of the world's largest social data providers (acquired by Twitter in 2014). We use this data for our analysis of tweet content, tweet format, and some controls on account activity and popularity.

Our financial data comes from six sources. Financial statement and stock data are from Compustat and CRSP, respectively. Earnings announcement dates and times come from Compustat and I/B/E/S, respectively. Release dates and times of annual reports (10-K), quarterly reports (10-Q), and 8-K filings are extracted from WRDS SEC Analytics Suite. Institutional ownership data are from WRDS SEC Analytics Suite-13F Holdings. By using this institutional ownership data set, we adjust for certain holdings omissions from Thomson Reuters 13F during our sample window, though this limits tests on institutional ownership to July 2013 onward.[6] Finally, we collect news event data from RavenPack Full Edition.

We require all observations to have (1) tweeted at least once before or on the given day, and (2) all Twitter and financial control variables. After imposing these restrictions, our final sample contains over 12.8 million tweets across 1.2 million firm-trading days.

3.2 Measures

3.2.1 Tweet measures

All tweet measures are calculated at the daily or the tweet level. Daily measures are calculated based on trading days with a 4:30pm cutoff in the Eastern Time Zone. Our first tweet measure, Tweets, is an indicator variable showing whether the company tweeted on a given day. We construct a similar measure, FinancialTweets, that indicates when a company has tweeted on a given day and at least one of the tweets contains text that is primarily financial in nature. To construct this measure, we use a machine learning algorithm to examine the content of each tweet.

The algorithm we use for tweet categorization is the Twitter-LDA algorithm of Zhao et al. (2011). This algorithm is based on the Latent Dirichlet Allocation (LDA) algorithm of Blei, Ng, and Jordan (2003), which has been adopted recently by several accounting studies (Bao and Datta,

[6] See the December 2016 WRDS research note 'Research Note Regarding Thomson-Reuters Ownership Data Issues'.

2014; Brown, Crowley, and Elliott, 2017b; Crowley, 2016; Hoberg and Lewis, 2017). The LDA algorithm provides a way to categorize the thematic content, or topics, within documents in an automated, researcher bias-free manner. Twitter-LDA extends the basic model to work with shorter 'documents' in the form of tweets, short text snippets of at most 140 characters, by incorporating correlations between words across Twitter users. We run this algorithm to detect 60 topics among the companies' tweets. We then manually classify the topics, identifying one topic that discusses financial information, eight topics discussing other business information, 34 topics on marketing (support, conferences, and other marketing), and 17 on other topics. As our primary focus is on financial tweets, our analysis is primarily focused on tweets matching the financial topic. However, our results are generally consistent when examining the broader collection of business tweets. Details of the Twitter LDA output are presented in Appendix B.

To test our second hypothesis, we examine the use of formatting in tweets. There are two primary ways to add extra content to a message on Twitter: adding media (an image or video) or adding a link to another webpage. As theory does not distinguish between these two format choices, we combine them into one measure, Format, which is an indicator variable equal to 1 if a tweet with media or a link is present on a given day, and 0 if all tweets are plain-text. We also extend format to Format|Financial, an indicator showing whether a financial tweet on a given day contains media or a link.

We derive some controls from the Twitter data to control for the level of involvement the company has shown on Twitter. We include an indicator variable showing whether a company has a verified account, Verified. Verified accounts have been vetted by Twitter for their authenticity and are 'an account of public interest'.[7] We also include measures to capture the number of

[7] For more information about verified accounts, see: https://twitter.com/verified.

followers a company has and how many accounts they were following, Followers and Friends, respectively. These measures capture the popularity of the Twitter account. Lastly, we include a measure of the total number of tweets the company posted during our sample period, Total_Tweets. These metadata items related to the time the data was pulled, as Twitter does not provide historical user account metadata. We also construct one other control variable, Recent_Tweets, the percentage of days that the company had posted on Twitter over the prior week (5 trading days). Both Total_Tweets and Recent_Tweets are intended to capture companies' level of activity on Twitter: overall activity and recent activity, respectively.

3.2.2 Event measures

Our primary event measures are earnings announcements from Compustat Quarterly, and 10-K, 10-Q, and 8-K filings from WRDS SEC Analytics Suite. When we extend our event analysis to an intraday setting, we use I/B/E/S to identify the time of release of earnings announcement. Due to data availability in I/B/E/S, our intraday tests have significantly smaller sample sizes than our other tests. For some tests we extend our events using news events derived from RavenPack's list of articles for each company in our sample. We filter on articles with a relevance of at least 75 out of 100 (articles that are highly related to the company). We also filter out duplicates by 'RP_STORY_ID'.

To categorize the articles into news types, we filtered the 2,064 news types of the Ravenpack Entity Mapping File into 15 topics which we expect to be relevant to companies' Twitter disclosures, covering 146 of the 2,064 news types in Ravenpack. We drop all other news types, and we later retain only news types that occur at least once per year per firm, on average, leaving us with six news events: M&A excluding rumors (Merger), financial information related to earnings or revenues (Financial), management forecasts (MgmtForecast), executive

announcements (Executive), analyst forecasts (Analyst), and executive trades (ExecTrade). We further classify financial news as positive (negative, neutral) if the news is indicative of earnings or sales increasing (decreasing, remaining unchanged). This classification was based on the topic of the article rather than its sentiment. Full descriptions of the components of each category and the decomposition of financial news into positive, negative, and neutral are presented in Appendix C.

To construct our measures of each news event type, we group events into three-day windows centered around trading days (–1, +1), using a 4:30pm Eastern Time Zone cutoff as before. We then construct indicators for each news type, where the indicator takes a value of 1 if there is at least one article of the given type in the window, and 0 otherwise. For financial information, we also construct measures for positive news (Pos_News_Financial), negative news (Neg_News_Financial), and neutral news (Neu_News_Financial). These measures indicate whether the financial news within the window is predominantly negative or positive. A company is classified as having positive (negative) financial news if the count of all positive financial news articles is greater (lesser) than the count of all negative news articles. If the amount of positive and negative news for a company is equal, or the sign of the news is ambiguous, then it is classified as neutral.

We replicate all tests using our measure of positive and negative news with measures based on market model cumulative abnormal returns (CAR) to validate our results. We classify any returns as neutral if the three-day return is within one standard deviation (firm-year specific) of zero. We classify returns as positive (negative) if the three-day CAR is 1.645 standard deviations above (below) zero (i.e., if the returns are outside a 90% confidence interval).

3.2.3 Financial measures

We use filing dates to identify days where there may have been more focus on companies' disclosures. We examine earnings announcements and three filing types: 10-K, 10-Q, and 8-K filings. For earnings announcements, we use a (-1,+1) trading day window around the announcement date from Compustat. For the SEC filings, we follow the same procedure as followed for news events, using a (-1,+1) trading day window with a 4:30 pm Eastern Time Zone cutoff, the time of filing release coming from WRDS SEC Analytics.

We construct the first measure of attention, institutional ownership, from WRDS SEC Analytics–13F Holdings by dividing the total institutional holdings per company by the number of shares outstanding reported in CRSP. In our attention test, we split the sample into high and low institutional ownership using a median split. The second measure of attention, feedback, is an indicator variable equal to 1 when a financial tweet receives a like or a retweet of a past event of the same type, which included a financial tweet, and 0 otherwise.[8]

As different types of companies may use Twitter differently, we include a standard list of financial control variables in all regressions. These variables include companies' most recently reported firm size (log of assets, Size), return on assets (ROA), market-to-book ratio (MB), debt to assets (Debt), and return volatility over the past month (21 trading days, Volatility).

All variables are defined in Appendix A.

4 Empirical methodology and results

4.1 Methodology

4.1.1 Timing test (H1)

[8] We do not include replies as they are not tracked or included in the data from the Twitter API or the GNIP.

To investigate tweet timing, we construct a daily dataset of the measures described in Section 3.2. We use probit regression to examine the impact of various events on firms' daily tweeting behavior, as given by equation (1).

$$\Phi^{-1}(Tweets_{i,d}) = \alpha + \boldsymbol{\beta_1} \cdot \boldsymbol{Events_{i,d}} + \boldsymbol{\beta_2} \cdot \boldsymbol{Twitter\_Controls_{i,d}} + \boldsymbol{\beta_3} \cdot \boldsymbol{Financial\_Controls_{i,d}} + \varepsilon \quad (1)$$

In equation (1) (where i represents firms and d represents trading days), the dependent variable is one of two related tweet measures: whether the firm posted a tweet on a given trading day, and whether the firm posted a financial tweet on a given trading day. In our tables, we only present the results for financial tweets, as we are mainly interested in financial events. We check the robustness of our tests with general tweets. The events of interest are: (1) a set of three indicators for standard accounting events (earnings announcements, annual/quarterly reports, and 8-K filings); (2) a set of indicators for the six news events identified in Section 3.2.2; (3) a set of three indicators showing whether there was financial news about the company, and if such news was positive or negative; and (4) a set of indicators (positive, negative, neutral) for abnormal returns around the trading day. To control for companies' level of Twitter involvement, we control for whether the account is verified, the number of followers the company has, the number of accounts the company is following, and the number of tweets posted over the past week and in total per company. For financial controls, we include measures of firm size, return on assets, market-to-book ratio, debt ratio, and stock return volatility. We also include year fixed effects and month fixed effects (as Twitter activity in general rapidly increased during the sample period) and industry fixed effects (as some industries, such as technology, are more likely to tweet in general). For industry fixed effects, we use the GICS sector. For some tests, we further split this sample based on whether an earnings announcement, 10-K or 10-Q filing, or 8-K filing is released in a

three-day window. For these tests, we compare each subset against days in which none of the events occurred in a three-day window to control for baseline firm behavior.

For intraday tests, we restrict our dependent variable to 1 during certain windows around events. For our before-event tests, we restrict the measure to 1 only within the three hours before an earnings announcement or filing is released. For our after-event tests, we restrict the measure to 1 within the three hours after an earnings announcement or filing is released. For our baseline comparison, we restrict the dependent variable to 1 when a tweet was not released within a six-hour window around the event.

4.1.2 Format test (H2)

We use probit regression on firm-trading day data to examine which factors affect firms' use of media and links in their tweets. For these regressions, we restrict our analysis strictly to firm-trading days with at least one tweet.

$$\Phi^{-1}(Format_{i,d}) = \alpha + \boldsymbol{\beta_2} \cdot \boldsymbol{Events_{i,d}} + \boldsymbol{\beta_3} \cdot \boldsymbol{Twitter\_Controls_{i,d}} + \boldsymbol{\beta_4} \cdot \boldsymbol{Financial\_Controls_{i,d}} + \varepsilon \quad (2)$$

In equation (2) (where i represents firms and d represents trading days), the dependent variable is Format. We examine two specific formatting decisions: whether a firm includes images or media in a tweet, and whether a firm includes a link to an external website. As we have no theoretical reason to differentiate between the two, we combine them into one measure (whether either occurred in a tweet on a given trading day). In robustness tests, we find similar results when testing media and link inclusion separately. Events, Twitter_Controls, and Financial_Controls include the same measures as in the tweet timing regressions. As with the timing tests, we include fixed effects for year, month, and industry, and in some tests we restrict our sample around earnings announcements or filings or we restrict our dependent variable to 1 during certain periods around these events.

4.1.3 Attention test (H3)

We use both equations (1) and (2) to examine how the discretionary choice of timing and format varies with the attention that firms receive. We partition our sample based on institutional ownership, and we separately include a measure of lagged feedback within accounting event. We expect the results to be stronger for the subsample with low institutional ownership and expect feedback from Twitter users to have a positive influence disclosure and formatting on Twitter.

4.2 Results

4.2.1. Determinants of adopting Twitter

The S&P 1500 firms in our sample period is comprised 1,639 firms with sufficient financial information (including those in and out of the index in the sample period). Among these firms, 453 either have no Twitter account or have never tweeted from their account. We first explore the factors driving the decisions to create a company Twitter account and to use it to send at least one tweet. It is potentially important to control these factors in our disclosure regressions. We run a probit model with a set of firm specific variables as controls, including year, month, and industry fixed effects. We find that size and market-to-book ratio are positively significantly associated with the likelihood of having and using a corporate Twitter account. This suggests that large and growth firms are more likely to have Twitter accounts.

4.2.2 Timing tests (H1)

We use daily windows to test firms' timing of tweets. Table 1 presents the summary statistics of our daily measures. The sample consists of 1,229,735 daily observations, where 65.5% of firm-days involve at least one tweet, and 3.38% of firm-days involve a financial tweet. Among the events we study, the most frequent event is the 8-K filing, followed by earnings announcements

and annual or quarterly reports. Of news events, the most common is executive trading, followed by analyst reports and financial news.

Verified Twitter accounts tend to be older and represent 28.2% of total observations. It is unclear, however, whether most firms' accounts are not verified because they did not seek out verification or because Twitter had denied their request for verification. For those accounts that are not verified by Twitter, we verified company ownership. The number of followers and accounts followed are highly skewed, as the median observation has 4,339 followers and is following 535 accounts, while the mean observation has 98,695 followers and was following 2,659 accounts. Likewise, tweeting activity tends to be skewed, as the median and mean observations have 2,059 and 6,304 tweets in total, respectively. As these controls are highly skewed right, we include the natural logarithm of all count-based twitter controls in the regressions rather than the raw counts.

We also examine the correlations between independent variables and controls. We note that financial tweets are positively correlated with all event types (earnings announcements, filings, and news). Although many correlations are statistically significant, the magnitude is generally smaller than 0.1.

Figure 1 presents the distribution of tweets within the week and within the day. In Panel A, we see that all tweets are more prevalent when the market is open, peaking during opening hours and dropping shortly after closing. Relative to financial tweets, there is also an increase in all tweets during the day on Saturday and Sunday, but this increase has a little less than half the magnitude of the weekday increases. For financial tweets, we see an even stronger concentration in opening hours, with a faster drop after the market closed and very little activity on weekends. In Panel B, we see that for financial tweets there is a run-up before trading hours, a peak between 10 and 11am (EST), a drop during the rest of the day, and a second peak just after the market

closed. The run-up and second peak coincide with hours in which earnings announcements, annual and quarterly reports, and 8-K filings are concentrated, as shown in Figure 2, which presents the distribution of accounting events by hour throughout the week (Panel A) and day (Panel B). The examined accounting events are only found on weekdays, and are largely concentrated in the 3.5 hours before trading and 1 hour after trading.

The regression testing Hypothesis 1a is presented in Table 2. Table 2 follows equation (1), where the dependent variable is an indicator of financial tweets. The results show that firms are more likely to post financial tweets around earnings announcements as well as annual and quarterly reports, consistent with Hypothesis 1a. For 8-K filings, we also find a higher likelihood of financial tweets. In Column 2, we replace 8-K filings with a vector of six news events, of which four (Merger, Financial, MgmtForecast, and Exec) are affected by the firm. For all four of these news events, we find a higher likelihood of financial tweets around these news events. This provides further support for Hypothesis 1a, showing that firms are more likely to post financial tweets around news coverage of financial events, M&A, management forecasts, and executive news.

Table 3 further presents the impact of major accounting events on tweeting behavior, splitting the sample into no event, earnings announcement, annual and quarterly reports, and 8-K filing windows. We then include indicators of neutral, negative, and positive financial news based on classifying Ravenpack articles. This model allows us to test Hypothesis 1b, which predicts that disclosures are concentrated around positive and negative news while less attention is paid to neutral news. Specifically, we expect to see an increase in financial tweets around both positive and negative news, but no increase around neutral news. Column 1 of Table 3, Panel A presents firms' tweeting behavior in the absence of the major accounting events of interest, indicating that the baseline is a positive relationship between financial tweets and neutral financial news. Columns

2 and $\Delta_{1,2}$ show that around earnings announcements, firms are no less likely to post financial tweets if news is neutral, but are more likely to post financial tweets around both positive and negative news. Columns 3 and $\Delta_{1,3}$ show the same pattern for annual and quarterly reports. For 8-Ks, we find an increase in the likelihood of posting a tweet if news is neutral and find larger increases around both positive and negative news. These results support Hypothesis 1b.

We conduct two robustness checks in testing H1b. First, we exclude those days with insignificant CAR days from Non-filing/Ann Dates in Column 1, and our results are robust. Second, we extend the above analysis using market reaction to classify the sign of news. The results are presented in Table 3, Panel B. Columns 2 and $\Delta_{1,2}$ show an increase (decrease) in financial tweet likelihood around earnings announcements with negative news (neutral news). Columns 3 and $\Delta_{1,3}$ show the same pattern with annual and quarterly reports. These results contradict the findings in Jung et al. (2017), which show that managers are less likely to disseminate bad news in the settings of earnings announcements. However, Columns 4 and $\Delta_{1,4}$ examine 8-K filings and show an increase in financial tweet likelihood around both negative and positive news along with a decrease in financial tweet likelihood around neutral news. These two checks provide additional support for Hypothesis 1b—that is, in general, firms disclose more financial news around the time when positive or negative news becomes public, although the daily results are sensitive to classification of good and bad news on days with earnings announcements and accounting filings.

Next, we examine the intraday timing of tweets to seek additional support for the hypothesis. Table 4 presents the intraday timing of financial tweets around a pooled set of earnings announcements, annual and quarterly reports, and 8-K filings. Panel A presents the results from news classification based on Ravenpack. Compared to the baseline in Column 1, we see that

financial tweets are more likely to be posted in the three hours before a major accounting event when the news is positive or negative. In the three hours after the event, we find increases for all news types, but find larger increases among good and bad news events. Panel B extends this analysis using CAR to classify the sign of news. We find an increase of financial tweets for both positive and negative news in the three hours before and after the accounting events. Overall, these results indicate that firms time their financial tweets in conjunction with their other disclosures, with both a run-up before the disclosure and a peak after, particularly when the news events are negative or positive rather than neutral.

4.2.3 Format tests (H2)

To test Hypothesis 2, we examine how firms' use of formatting on Twitter varies with accounting events. Summary statistics of format in Table 1 shows that firms include media and/or a link in a tweet on 59.4% of all days (90.7% of all days with tweets). Firms post a financial tweet with formatting on 2.83% of all days (83.7% of all days with financial tweets).[9]

The regression testing Hypothesis 2a is presented in Table 5. We find that both earnings announcements and accounting filings are associated with an increase in financial tweets including media and links, consistent with Hypothesis 2a. Financial tweets with format do not increase with 8-K filings. However, when we replace 8-K filings with news events, we again find a positive relationship between all four events controlled by the firm and the use of media and links in tweets. Specifically, firms are more likely to include media and links in financial tweets around news coverage of financial information, M&A, management forecasts, and executive information, further supporting Hypothesis 2a.

[9] This number is similar to that reported in Blankespoor et al. (2014), who examine a much smaller set of firms (IT firms) and find that, on average, 75.4% of tweets in their sample contain hyperlinks.

The regressions testing Hypothesis 2b are presented in Tables 6 and 7. In Table 6, we show how format use in financial tweets is related to financial news sign around major accounting events. Panel A presents the results from news classification based on Ravenpack. Columns 2 and $\Delta_{1,2}$ show an increase in the use of formatting around earnings announcements with positive or negative news. Columns 3 and $\Delta_{1,3}$ indicate that the same pattern holds for financial tweets around annual and quarterly reports. Lastly, in columns 4 and $\Delta_{1,4}$, around 8-K filings we find increased formatting usage in financial tweets when there is neutral news and a larger increase in format usage in financial tweets when there is negative or positive news. These results are generally consistent with Hypothesis 2b, showing that having a clear direction of news increases the likelihood of including media or links in financial tweets.

Table 6, Panel B repeats the above analysis using CAR to classify news. Columns 2 and $\Delta_{1,2}$ show an increase in the likelihood of format use in financial tweets around earnings announcements with negative news. Columns 3 and $\Delta_{1,3}$ examine annual and quarterly reports and show an increase in format usage in financial tweets around both negative and positive news. Columns 4 and $\Delta_{1,4}$ examine 8-K filings and again show an increase in format usage in financial tweets around both negative and positive news along with a decrease in financial tweet likelihood around neutral news. Taken together, these results further support Hypothesis 2b—that firms in general are more likely to use media and links in financial tweets around accounting events when the news is positive or negative, but not when the news is neutral. The only exception is the earnings announcement setting, in which we do not observe an increase in format usage in financial tweets. As in the timing scenario, tweeting format around earnings announcements differs from tweeting format around other news events.

Table 7 presents the use of intraday format around pooled major accounting events. In

Columns 2 and $\Delta_{1,2}$ (3 and $\Delta_{1,3}$) of Panel A, we see that financial tweets are more likely to involve format for all news types in the three hours before (after) accounting events, and that the biggest increase is observed around positive and negative news events. Panel B shows the same results for positive and negative news events based on CAR, but no change in the three hours before neutral events and a decrease in format usage in the three hours after neutral events. These results indicate that firms use format in financial tweets in conjunction with the timing of their other disclosures, with both a run-up in format usage before the disclosure and a peak thereafter, particularly when the news events are negative or positive rather than neutral.

4.2.4 Attention tests (H3)

To test whether firms with limited attention from investors are more likely to exercise discretion, we revisit our analyses and split our sample based on institutional ownership, and separately include a measure of lagged feedback within accounting event. First, we perform a median split on institutional ownership. We use low institutional ownership firms to proxy for firms with less attention, and high institutional ownership firms to proxy for firms with more attention. Table 8 replicates the timing results from Table 2 splitting on institutional ownership. Columns 1, 2, and $\Delta_{1,2}$ show that low institutional ownership firms are more likely to post a financial tweet around earnings announcements, while high institutional ownership firms are more likely to post a financial tweet around annual and quarterly reports and 8-K filings. The results around earnings announcements are consistent with Hypothesis 3, with lower attention firms using Twitter to increase the visibility of their disclosures. The results around 10-K, 10-Q, and 8-K filings, however, are not consistent with Hypothesis 3; interestingly, they are consistent with extra oversight by institutional investors leading to more disclosure.

Columns 3 and 4 of Table 8 show how firms' use of formatting in financial tweets varies with the attention they receive. We find that low institutional ownership firms are more likely to include media and links in financial tweets around earnings announcements than high institutional ownership firms. This is consistent with firms using formatting to improve the visibility of their financial disclosures on Twitter when they receive less attention in general. Consistent with the results in Columns 1 and 2, we find that high institutional ownership firms are more likely to include formatting in financial tweets around annual and quarterly reports and 8-K filings.

We next examine the impact of a unique feature of social media, feedback. Users are able to provide direct feedback to a tweet through three main interactions. They can like a tweet, which increases a counter indicating the number of users that have liked said tweet; they can retweet, sharing the tweet with their own followers and incrementing a separate retweet counter; and, finally, they can reply to the message on Twitter, providing a message tied to the specific tweet to the company. Using all three methods, investors show that they pay attention to a company's tweets.

To test the limited attention hypothesis using feedback feature, we aggregate two of the three feedback methods (likes and retweets) into a binary measure, Feedback, equal to 1 when at least one method was used in response to a past event of the same type, including a financial tweet, and 0 otherwise. We explicitly examine whether feedback affects firms' subsequent disclosure behavior, shedding light on whether attention from investors can affect disclosure behavior in the future.

We test for each event type in our study to determine whether feedback around a previous event of the same type, Feedback_lag, influences the likelihood of a firm providing a financial tweet around an event, and whether feedback influences firms to use formatting within financial

tweets around events conditional on having tweeted around the events. Table 9 shows the results. We find that feedback on financial tweets around earnings announcements, 10-K and 10-Q filings, and 8-K filings all reinforce firms' behavior in the future (i.e., increasing the likelihood of financial tweets around subsequent events of the same type). These results suggest that the feedback mechanisms on Twitter dynamically affect firms' disclosure patterns on the platform. Furthermore, we find that firms are more likely to use formatting in financial tweets around subsequent disclosures in response to feedback on Twitter. In untabulated tests, we find that feedback also positively impacts financial tweeting and format usage across event types and on non-event days in the period after a disclosure. Taken together, these findings suggest that attention from investors does indeed lead firms to adopt a more proactive disclosure strategy on Twitter.

4.3 Robustness

We conduct a large battery of robustness checks to validate the consistency of our results before and after the SEC ruling in April 2013, and to prove that our results hold for accounting events that occur during trading hours, that they are not affected by the presence or lack of specific IR Twitter accounts for firms, that they are consistent when leveraging both our measures of positive and negative news simultaneously, and that our results on formatting are not affected by endogeneity due to censoring or by combining URL and media usage into one construct. We summarize the results of these tests below.

SEC ruling in 2013: To examine the impact of the SEC ruling in April 2013, we split our sample into post- and pre-SEC periods with respect to April 2013 (while removing this month from our data). This robustness check validates our results under the current social media disclosure regime, and examines our results under the prior regime. Our results are almost identical in the post-SEC period. In the pre-SEC period, we find somewhat weaker results, with only earnings

announcements driving financial tweet posting and formatting in general, and with relatively limited impact of negative and positive news on intraday tweet timing.

Events during trading hours: We check the robustness of our results by restricting our sample to events that occurred during trading hours. Firms are expected to be more likely to act during trading hours, when investors can react to tweets immediately. Our results are inferentially similar, with the exception that we do not observe any difference in the intraday timing of financial tweets around positive news measured by CAR. This difference may be driven by the exclusion of most earnings announcements, given that most are released between 8 and 9 am and just after 4 pm (i.e., just before or just after the market's opening hours, see Figure 2).

Multiple Twitter Accounts: One concern with our sample selection is that some firms operate a separate Twitter account specifically for IR, which could weaken our results if these accounts are not identified and analyzed. In July 2017, we checked to see if each firm that had been in the S&P 1500 from 2012 to 2016 had a separate IR Twitter account. Across all firms, we found only 11 such accounts. Furthermore, we found that 862 of 1,443 firms with Twitter accounts had a link to their main Twitter account on their IR website, and that of the 11 with separate IR Twitter accounts, eight linked to their main Twitter account from their IR website, two did not have a Twitter link on their IR website, and only one linked to its IR account. Overall, these univariate results indicate that firms' primary Twitter accounts appear to be the most important Twitter accounts for IR. Furthermore, we find that our results are inferentially similar when we (1) removed the 11 firms with an IR Twitter account, (2) restricted our sample to the 862 firms that link their IR website to their main Twitter account, and (3) restricted our sample to the 581 companies that do not link their IR website to their main Twitter account.

Alternative news classification: To examine whether consistency in the direction of news between our Ravenpack-based and CAR-based classifications affected the results, we re-test all statistical tests relying on these measures with a set of hybrid measures. In particular, we replace negative and positive news with consistent (both positive or both negative) and inconsistent news (one positive and one negative). As expected, we find significant increases in the use of financial tweets and formatting in financial tweets when news is both consistent and inconsistent across two classifications. Consistent news is unlikely to be interpreted as neutral news, and thus should lead to greater disclosure according to our theory. Inconsistency cannot be interpreted as neutral; the disagreement is also likely to lead to greater disclosure.

Endogeneity and the usage of different types of format: To control for potential endogeneity in format tests due to censoring of Format (as format is only observable when a company tweets), we implemented a probit model with sample selection. This model uses a probit regression with an instrumental variable to model the likelihood of a tweet in the first stage, and then uses a probit regression to model the likelihood of using media or a link in the second stage. We use the number of accounts the company follows as the instrument, as we have no theoretical basis to assume a causal link between tweet formatting and following other accounts. We do not include this instrument in the second stage regression. Using this regression specification, we find inferentially similar results, suggesting that our conclusions are not affected by endogeneity due to firms' choice of when to tweet. We also individually test our format results using disaggregated measures (URL and media separately), and find that our inferences remain unchanged and that both format choices are used similarly by companies around accounting events and news events.

4.4. Reconciling puzzling divergences between Jung et al. (2017) and this study

We find that managers are more likely to post financial tweets around the time of earnings announcements, 10-Q/10-K filings, and 8-K filings regardless of whether new events are negative or positive. In particular, regarding earnings announcements, we find that managers are more likely to post financial tweets when the announcements are significantly negative when the direction of news is measured by CAR(-1,1). Such a pattern of information dissemination on Twitter contradicts the findings of Jung et al. (2017). In this forthcoming paper, Jung et al. (2017) concludes that firms are less likely to disseminate news when earnings announcements are negative. We thus conduct a battery of tests to reconcile the puzzling divergences between the two studies as a part of scientific inquiry. The results are reported in the online appendix.

We notice several significant visible differences between two studies. First, the period and size of our sample are quite different although both studies are based on S&P 1500 firms. The sample of Jung et al. (2017) consists of tweets from the first quarter of 2010 to the first quarter of 2013. By the end of their data collection period, only 52 percent of the S&P 1500 firms had adopted one type of social media account or the other. Our sample consists of 12.8 million tweets from 1,215 S&P 1500 firms in the period January 2012 to December 2016. Second, Jung et al. (2017) use a dictionary approach to identify earnings announcement related tweets while we use a machine learning approach to identify financial tweets. In this reconciliation test, we also use a dictionary approach following the search strategy identified in footnote 7 of Jung et al. (2017). Third, Jung et al. (2017) use earnings surprise to classify good or bad news as they focus solely on earnings announcements, while we use both RavenPack and CAR(-1,1) to classify good or bad news.

Due to limited data availability, we are not able to examine the effect of the first difference, i.e., whether sample selection bias [early vs. late adopters] and sample size would affect our

conclusions. Timing of adoption of Twitter may be correlated with different types of firms. One could expect the incentives of discretionary behavior to change over time, particularly after the SEC paid attention to information disclosure on social media and issued its new guidance in April 2013. Regarding the third difference on the measures of good or bad news, we expect earnings surprises, if measured correctly, to be captured by CAR(-1,1) even if one thinks Ravenpack is a noisy measure. However, as Jung et al. (2017) focus on earnings announcements and classify earnings surprises as "bad or not bad" based on whether earnings is below analysts' consensus or not while we classify news group into "bad, neutral, and good" and examine a broader collection of significant news events (earnings announcements, 10-K, 10-Q, and 8-K), the results should not be compared mechanically.

We thus focus on the effect of the second difference in this reconciliation test. We replicate all the tests presented above using a dictionary approach. We first examine the agreement between the machine learning-based LDA and dictionary approaches. Panel B of Table A1 in the online appendix presents a 2x2 matrix of financial tweets classified by two approaches. Only 1.25% tweets are classified as financial by both approaches, and 9.15% tweets are classified as financial tweets by the dictionary approach but not by LDA. However, only 2.13% of tweets are classified as financial tweets by the LDA approach but not by the dictionary approach. The statistics suggest that the LDA approach is more precise. Panel C presents the percentage of tweets around financial events by financial tweet measure. Across all three major events, the LDA approach generated higher percentages of tweets around these events, again suggesting that the LDA approach is more powerful.

Next, we reclassify the financial tweets using the dictionary approach and repeat all the tests in the paper. Table A2 in the online appendix shows that, using the dictionary measure,

managers still appear to be more likely to post financial tweets around the time of earnings announcements, accounting filings, and 8-K filings.

Moreover, we replicate the sample cuts discussed in Jung et al. (2017), examining litigation, then number of retail investors, and the number of followers Twitter accounts had. Each split is effected on the median of the measure. We then test the decision to release a financial tweet (classified using our LDA approach) related to good or bad news in conjunction with these sample splits. For earnings announcements, we find that when news is classified by CAR(-1,1), firms with high litigation risk are not less likely to disclose bad news (see Panel B of Table A3), contradicting the findings in Jung et al. (2017). This finding is robust to news measured by Ravenpack (Panel A of Table A3). The results for 10-Q/10-K filings and 8-K filings are quite similar.

While we cannot determine the exact reasons driving the seemingly different results between the two studies, we believe that our large-sample machine learning-based analysis sheds new light on firms' discretionary actions on social media.

5. Conclusions

This paper examines whether firms make discretionary choices regarding the types of events, timing, and disclosure format used when they disclose news on Twitter. Using a large sample of tweets generated by S&P 1500 firms, we found that firms' tweet timing is positively associated with major accounting events and corporate news events, and that this effect is strongest around news with a clear positive or negative direction. We also found that inclusion of multimedia (image and video) or hyperlinks in financial tweets is positively associated with major accounting events and corporate news events, and that the inclusion of media or links in financial tweets is most frequent around news with a clear positive or negative direction. Furthermore, both the timing and usage of formatting in financial tweets are clustered in the three hours before and after major

accounting events, and this clustering is strongest around news with a clear positive or negative direction. Finally, firms with limited attention from investors post more financial tweets and include more media and links around earnings announcements, while firms with more attention post more financial tweets around 8-K filings. Importantly, we found that use of the feedback feature on Twitter may affect firms' disclosure behavior dynamically and lead them to be more proactive in using Twitter to enhance their disclosures.

Our study is among the first to document firms' discretionary disclosure choices on Twitter around a diverse set of information events and accounting filings. Our empirical findings provide support for the classic voluntary disclosure theory in the new era of social media. The evidence suggests that managers exercise discretion regarding the level, timing, and format of disclosure on social media and that these choices are determined in conjunction with investors' expectations. Moreover, our study addresses the issue brought up by Miller and Skinner (2015), who suggest that the emergence of social media not only provides firms a new way of disseminating information, but that the interactive features of social media also brings new challenges for firms to manage their information environment. By highlighting firms' discretionary choices regarding tweet formatting and timing in coordination with other information events and accounting filings, our approach provides new insights into both the mechanism by which firms can take advantage of new technologies in their disclosure practice and the capital market consequences of such practice. Again, as McLuhan understood, the media are 'make-happen agents' and not 'make-aware agents'; habits of mind are derived from our use of media—'we become what we behold … we shape our tools and afterwards our tools shape us' (McLuhan, 1964).

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A Variable definitions

Panel A: Dependent variables

Variable	Definition
$FinancialTweets$	An indicator equal to 1 if at least 1 of the Company's tweets discusses financial information on a given day, 0 otherwise (Twitter API).
$Before\|Financial$	An indicator equal to 1 if a financial tweet was released by the company during the 3 hours before an event.
$After\|Financial$	An indicator equal to 1 if a financial tweet was released by the company during the 3 hours after an event.
$Before\|Format$	An indicator equal to 1 if a financial tweet containing media or a hyperlink was released by the company during the 3 hours before an event.
$After\|Format$	An indicator equal to 1 if a financial tweet containing media or a hyperlink was released by the company during the 3 hours after an event.
$Format\|Financial$	An indicator equal to 1 if a financial tweet by a company on a given day contains a hyperlink or media.

Panel B: Independent variables

Variable	Definition
$Earnings\_Ann$	An indicator equal to 1 if an earnings announcement was released during the (-1,+1) window around a given trading day, 0 otherwise (Compustat Quarterly).
$Form\_10\text{-}K, 10\text{-}Q$	An indicator equal to 1 if a 10-K or 10-Q filing was released during the (-1,+1) window around a given trading day, 0 otherwise (WRDS SEC Analytics Suite).
$Form\_8\text{-}K$	An indicator equal to 1 if an 8-K filing was released during the (-1,+1) window around a given trading day, 0 otherwise (WRDS SEC Analytics Suite).
$Feedback\_lag$	An indicator equal to 1 when a financial tweet received a favorite, retweet, or reply on the previous announcement.
$News\_[Event]$	News indicator regarding an event $[Event]$, based on hand classification of Ravenpack's news event taxonomy. Specific events are detailed in Appendix C.
$Neu\_News\_Financial$	An indicator equal to 1 if the financial articles in a 3 day window centered on the day of interest are neutral (Ravenpack).
$Neg\_News\_Financial$	An indicator equal to 1 if there are more negative financial articles in a 3 day window centered on the day of interest than there are positive financial articles (Ravenpack).

Panel B: Independent variables

Variable	Definition
$Pos\_News\_Financial$	An indicator equal to 1 if there are more positive financial articles in a 3 day window centered on the day of interest than there are negative financial articles (Ravenpack).
$Neu\_CAR_{(-1,+1)}$	An indicator equal to 1 if $CAR_{(-1,1)}$ is within 1 standard deviation (firm-year) of 0.
$Neg\_CAR_{(-1,+1)}$	An indicator equal to 1 if $CAR_{(-1,1)}$ is below -1.645 standard deviations (firm-year) from 0 (bottom 5%).
$Pos\_CAR_{(-1,+1)}$	An indicator equal to 1 if $CAR_{(-1,1)}$ is above 1.645 standard deviations (firm-year) from 0 (top 5%).

Panel C: Control variables

Variable	Definition
$Verified$	An indicator equal to 1 if the company's Twitter account has been verified, 0 otherwise (Twitter API).
$Followers$	The number of Twitter followers the Company's Twitter account has (Twitter API).
$Friends$	The number of Twitter friends the company has, i.e., the number of accounts the Company's Twitter account is following (Twitter API).
$Recent\_Tweets$	The number of tweets in the 5 trading days (1 week) leading up to the current day (Twitter API).
$Total\_Tweets$	Total number of tweets the company posted through the end of the sample period, December 31, 2016 (Twitter API).
$Size$	Natural logarithm of company's total assets (Compustat: at).
ROA	Company's return on assets calculated as net income (Compustat: ni) divided by total assets (Compustat: at).
MB	Market to book ratio, calculated as shares outstanding (CRSP: $shrout$) times shares price (CRSP: prc) divided by book assets (Compustat: at).
$Debt$	Most recent annual long term debt (Compustat, lt) divided by most recent annual long term assets (Compustat at).
$Volatility$	Company's stock return volatility over the past month (21 trading days, CRSP).

B Twitter topics

The following table displays the top 10 words per hand categorized topic. Each of the topics below is comprised of one or more similar topics from the Twitter-LDA algorithm.

Categorization	Subtopic	Top 10 words
Business	Financial (1)	market, growth, markets, trading, earnings, global, report, quarter, results, energy
	Other Business (8)	#jobs, dm, email, #job, hear, send, contact, hiring, working, details
Marketing	Support (5)	dm, store, customer, team, flight, send, number, hear, feedback, claim
	Conference (5)	booth, join, today, #iot, learn, great, live, week, register, stop
	Other Marketing (24)	pass, free, enjoy, shipping, heres, life, love, time, #apple, shop
Other	Other (17)	stay, travelers, dont, rating, order, joe, tweet, collection, enjoy, book

When categorizing tweets, we map each tweet to one of the 60 topics generated by the Twitter-LDA algorithm. We then map those 60 topics to the aggregations used in the paper. Consequently, if a tweet categorized as 40% of a business topic, 30% of a marketing topic, and 30% of other, it will be categorized as a business tweet, as its most prevalent topic is in the business category.

C News event categorization

We identified 15 news event types from the Ravenpack Entity Mapping File. Of those 15, we retain 6 events that occur at least once per year per firm, on average. The 9 events dropped include: Auditor changes, bankruptcy, exchange related events (delisting), fraud, illegal trading, government investigation, joint ventures, legal settlements, and spinoffs. The remaining 6 events cover 146 of the event categories out of the 2,064 event categories in the Entity Mapping File. The below table details the events included in each of our news event indicators.

Event	Event categories included
$News\_Financial$	Comparisons or announcements of earnings, EBIT, EBITA, EBITDA, revenue or gross profit; EPS; earnings revisions
$News\_Merger$	All company acquisition, merger, and unit acquisition categories except rumors; stake changes
$News\_MgmtForecast$	Management forecast of earnings, EBIT, EBITA, EBITDA, revenue or gross profit; forecast suspension
$News\_Exec$	Executive changes; compensation; health; scandals
$News\_Analyst$	Earnings and revenue estimates and rating changes
$News\_ExecTrade$	Executive trading on company's stock

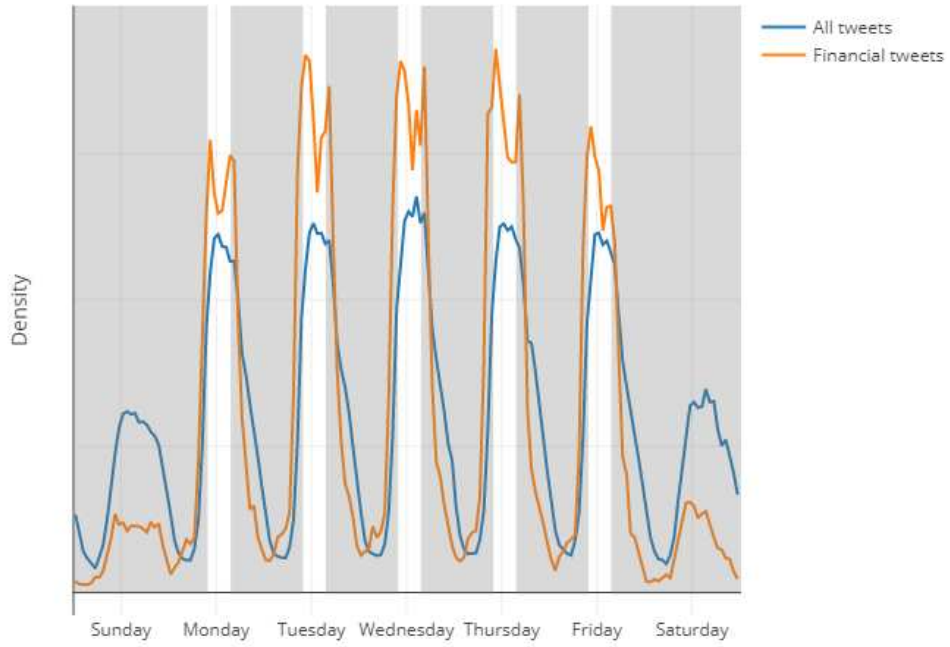
We further decompose $News\_Financial$ into three parts based on the sign of the news: Negative, Neutral, and Positive. We identify the sign of the news from the "property" field in Ravenpack, using the following classification:

Negative	Neutral	Positive
Revised down	Revised	Revised up
Below expectations	Announced	Above expectations
Delayed		Meets expectations
Negative		Positive
Down		Up

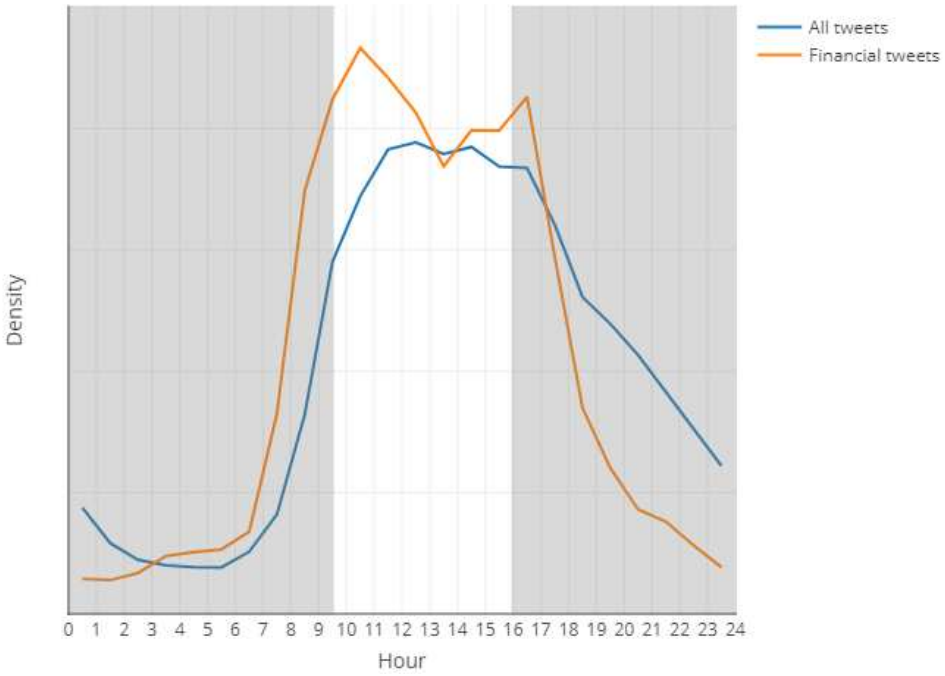
Figures

Figure 1: Distribution of tweets by time

Panel A: Tweets by hour within week



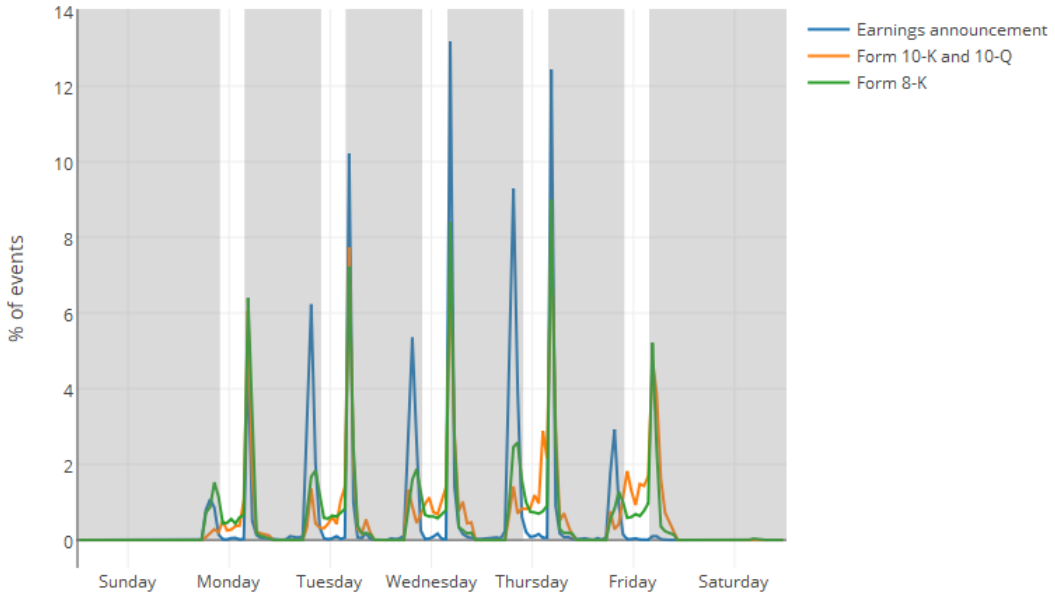
Panel B: Tweets by hour within day



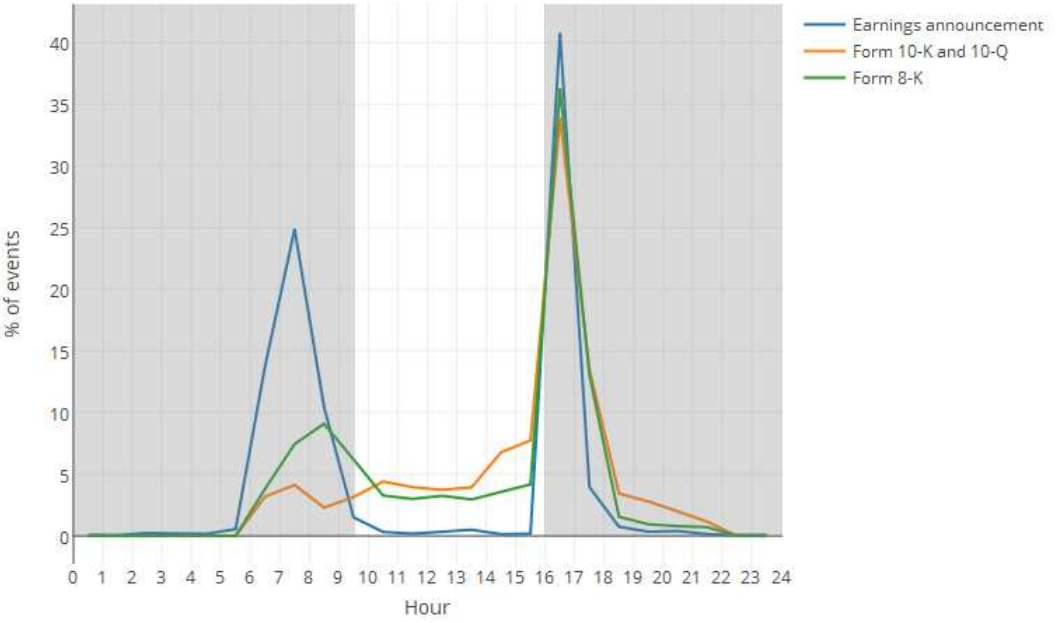
This figure shows the distribution of companies' tweets and financial tweets by hour of the week and hour of the day. The background is white during hours when the NYSE is open and gray when it is closed.

Figure 2: Distribution of accounting events by time

Panel A: Accounting events by hour within week



Panel B: Accounting events by hour within day



This figure shows the distribution of companies' earnings announcements, annual and quarterly reports, and 8-K filings by hour of the week and hour of the day. The background is white during hours when the NYSE is open and gray when it is closed.

Tables

Table 1: Descriptive statistics

	Mean	Median	SD	p10	p90
$Tweets$	0.655	1.00	0.475	0	1.00
$FinancialTweets$	0.0338	0	0.181	0	0
$Before\|Financial$	0.0010	0	0.0313	0	0
$After\|Financial$	0.0019	0	0.0440	0	0
$Format$	0.594	1.00	0.491	0	1.00
$Format\|Financial$	0.0283	0	0.166	0	0
$CAR_{(-1,1)}$	-0.0001	0.0005	0.0351	-0.0303	0.0300
$Inst$	0.885	0.942	0.147	0.682	1.00
$Earnings\_Ann$	0.0475	0	0.213	0	0
$Form\_10\text{-}K, 10\text{-}Q$	0.0475	0	0.213	0	0
$Form\_8\text{-}K$	0.143	0	0.350	0	1.00
$News\_Merger$	0.0668	0	0.250	0	0
$News\_Financial$	0.0935	0	0.291	0	0
$News\_MgmtForecast$	0.0325	0	0.177	0	0
$News\_Exec$	0.0563	0	0.231	0	0
$News\_Analyst$	0.0106	0	0.102	0	0
$News\_ExecTrade$	0.178	0	0.383	0	1.00
$Neu\_News\_Financial$	0.0323	0	0.177	0	0
$Neg\_News\_Financial$	0.0171	0	0.130	0	0
$Pos\_News\_Financial$	0.0440	0	0.205	0	0
$Neu\_CAR_{(-1,+1)}$	0.767	1.00	0.423	0	1.00
$Neg\_CAR_{(-1,+1)}$	0.0438	0	0.205	0	0
$Pos\_CAR_{(-1,+1)}$	0.0391	0	0.194	0	0
$Verified$	0.282	0	0.450	0	1.00
$Followers$	98695	4339	736019	424	104470
$Friends$	2659	535	19030	55.0	3678
$Recent\_Tweets$	0.655	0.800	0.388	0	1.00
$Total\_Tweets$	6304	2059	24136	268	11378
$Size$	8.26	8.15	1.79	6.07	10.6
ROA	0.0482	0.0464	0.0996	-0.0093	0.132
MB	1.50	1.07	1.56	0.237	3.11
$Debt$	0.569	0.565	0.252	0.253	0.871
$Volatility$	0.0179	0.0150	0.0124	0.0083	0.0297

The sample consists of 1,229,735 observations, except for all CAR measures at 1,186,801 observations and $Inst$ at 903,658 observations. Variable definitions for all variables are included in Appendix A. Methodology for Twitter topics is discussed in Appendix B, and methodology for news events is discussed in Appendix C.

Table 2: Tweeting activity

	(1) Financial *probit*	(2) Financial *probit*
$Earnings\_Ann$	0.469^{***}	0.360^{***}
$Form\_10\text{-}K, 10\text{-}Q$	0.0686^{***}	0.0442^{***}
$Form\_8\text{-}K$	0.0171^{**}	
$News\_Merger$		0.0552^{***}
$News\_Financial$		0.0926^{***}
$News\_MgmtForecast$		0.169^{***}
$News\_Exec$		0.0669^{***}
$News\_Analyst$		0.0200
$News\_ExecTrade$		-0.0034
$Verified$	0.0139^{**}	0.0200^{***}
$\log(Followers)$	0.0634^{***}	0.0605^{***}
$\log(Friends)$	-0.0437^{***}	-0.0418^{***}
$Recent\_Tweets$	0.931^{***}	0.934^{***}
$\log(Total\_Tweets)$	0.120^{***}	0.118^{***}
$Size$	-0.0077^{***}	-0.0147^{***}
ROA	0.305^{***}	0.290^{***}
MB	0.0294^{***}	0.0282^{***}
$Debt$	-0.172^{***}	-0.165^{***}
$Volatility$	1.87^{***}	1.60^{***}
$Cons$	-3.80^{***}	-3.72^{***}
$Year\ FE$	Included	Included
$Month$ FE	Included	Included
$Industry\ FE$	Included	Included
N	1229734	1229734
Pseudo R2	0.158	0.159

All regressions are run on the full day-basis sample. The dependent variable for all regressions is $FinancialTweets$, an indicator for if a company posted a financial tweet on a given trading day. Variable definitions for all variables are included in Appendix A. Methodology for Twitter topics is discussed in Appendix B, and methodology for news events is discussed in Appendix C.

Table 3: Timing of financial tweets to major accounting events

Panel A, News classification based on Ravenpack

	(1) Non-filing/Ann Dates *probit*	(2) Earnings Ann *probit*	$\Delta_{1,2}$ X^2	(3) 10-K, 10-Q *probit*	$\Delta_{1,3}$ X^2	(4) 8-K Filing *probit*	$\Delta_{1,4}$ X^2
$Neu\_News\_Financial$	0.106***	0.129***	0.250	0.0800*	0.280	0.166***	3.88**
$Neg\_News\_Financial$	0.0005	0.507***	166***	0.460***	119***	0.501***	210***
$Pos\_News\_Financial$	−0.0120	0.477***	285***	0.435***	226***	0.506***	480***
$Verified$	0.0105	0.0091	0	0.0324	0.560	0.0340**	1.60
$\log(Followers)$	0.0665***	0.0189**	35.0***	0.0276***	17.9***	0.0392***	22.3***
$\log(Friends)$	−0.0481***	−0.0110*	33.0***	−0.0078	28.9***	−0.0259***	22.9***
$Recent\_Tweets$	1.01***	0.564***	172***	0.725***	47.2***	0.722***	113***
$\log(Total\_Tweets)$	0.137***	0.0456***	73.2***	0.0760***	24.1***	0.0589***	94.8***
$Size$	−0.0174***	0.0993***	247***	0.0280***	28.5***	0.0254***	70.1***
ROA	0.358***	−0.0717	11.5***	0.137	1.83	−0.0594	19.8***
MB	0.0265***	0.0536***	18.0***	0.0257***	0.0100	0.0308***	0.760
$Debt$	−0.172***	−0.0938**	3.13*	−0.206***	0.470	−0.146***	0.610
$Volatility$	2.21***	−2.94***	26.1***	−4.31***	40.1***	−0.370	18.9***
$Cons$	−4.00***	−3.28***		−2.90***		−3.15***	
$Year\ FE$	Included	Included		Included		Included	
$Month$ FE	Included	Included		Included		Included	
$Industry\ FE$	Included	Included		Included		Included	
N	1014618	58397		58365		175885	
Pseudo R2	0.168	0.104		0.114		0.120	

Panel B, News classification based on cumulative abnormal return (CAR)

	(1) Non-filing/Ann Dates	(2) Earnings Ann	$\Delta_{1,2}$	(3) 10-K, 10-Q	$\Delta_{1,3}$	(4) 8-K Filing	$\Delta_{1,4}$
	probit	*probit*	X^2	*probit*	X^2	*probit*	X^2
$Neu\_CAR_{(-1,+1)}$	-0.0170^{**}	-0.0617^{***}	3.42^{*}	-0.0794^{***}	5.21^{**}	-0.0866^{***}	16.5^{***}
$Neg\_CAR_{(-1,+1)}$	0.0077	0.0598^{**}	2.80^{*}	0.139^{***}	11.2^{***}	0.162^{***}	34.0^{***}
$Pos\_CAR_{(-1,+1)}$	0.0249	-0.0164	1.66	0.0922^{**}	2.61	0.0984^{***}	7.10^{***}
$Verified$	0.0238^{***}	0.0064	0.440	0.0279	0.0200	0.0286^{*}	0.0700
$\log(Followers)$	0.0682^{***}	0.0179^{**}	38.8^{***}	0.0293^{***}	18.2^{***}	0.0456^{***}	15.5^{***}
$\log(Friends)$	-0.0466^{***}	-0.0072	36.8^{***}	-0.0094	24.4^{***}	-0.0237^{***}	23.6^{***}
$Recent\_Tweets$	1.02^{***}	0.547^{***}	193^{***}	0.689^{***}	63.9^{***}	0.690^{***}	149^{***}
$\log(Total\_Tweets)$	0.140^{***}	0.0474^{***}	72.9^{***}	0.0755^{***}	26.1^{***}	0.0600^{***}	97.7^{***}
$Size$	-0.0226^{***}	0.112^{***}	321^{***}	0.0236^{***}	28.2^{***}	0.0220^{***}	76.7^{***}
ROA	0.336^{***}	-0.103	12.1^{***}	-0.0357	5.36^{**}	-0.0557	16.2^{***}
MB	0.0268^{***}	0.0598^{***}	25.6^{***}	0.0278^{***}	0.0200	0.0342^{***}	2.27
$Debt$	-0.172^{***}	-0.131^{***}	0.850	-0.236^{***}	1.50	-0.168^{***}	0.0100
$Volatility$	2.15^{***}	-2.07^{**}	17.8^{***}	-5.87^{***}	55.8^{***}	-0.972^{*}	26.4^{***}
$Cons$	-3.99^{***}	-3.07^{***}		-2.45^{***}		-2.92^{***}	
$Year\ FE$	Included	Included		Included		Included	
$Month$ FE	Included	Included		Included		Included	
$Industry\ FE$	Included	Included		Included		Included	
N	979473	56364		56388		169286	
Pseudo R2	0.173	0.0858		0.0981		0.101	

Panel A examines news direction based on classifying Ravenpack articles, while Panel B uses a classification based on cumulative abnormal return (CAR). In each panel, regression (1) is run on the day-basis sample excluding (-1,+1) firm-day windows with earnings announcements, 10-K filings, 10-Q filings, or 8-K filings; regression (2) is run on the day-basis sample restricted to (-1,+1) firm-day windows around earnings announcements; regression (3) is run on the day-basis sample restricted to (-1,+1) firm-day windows around 10-K or 10-Q filings; regression (4) is run on the day-basis sample restricted to (-1,+1) firm-day windows around 8-K filings. The dependent variable for all regressions is $FinancialTweets$, an indicator for if a company posted a financial tweet on a given trading day. Column $\Delta_{1,2}$ shows the difference between columns (1) and (2) using a X^2 test. Column $\Delta_{1,3}$ shows the difference between columns (1) and (3) using a X^2 test. Column $\Delta_{1,4}$ shows the difference between columns (1) and (4) using a X^2 test. Variable definitions for all variables are included in Appendix A. Methodology for Twitter topics is discussed in Appendix B.

Table 4: Intraday timing of financial tweets to major accounting events

Panel A, News classification based on Ravenpack

	(1) Other *probit*	(2) Before *probit*	$\Delta_{1,2}$ X^2	(3) After *probit*	$\Delta_{1,3}$ X^2
$Neu\_News\_Financial$	0.156***	0.266***	1.68	0.490***	18.4***
$Neg\_News\_Financial$	0.161***	0.642***	70.8***	1.11***	317***
$Pos\_News\_Financial$	0.168***	0.614***	123***	1.04***	500***
$Verified$	−0.0185	−0.0493	0.370	0.0977***	6.32**
$\log(Followers)$	0.0528***	0.0327***	1.69	−0.0073	17.2***
$\log(Friends)$	−0.0365***	−0.0075	5.61**	0.0262***	31.4***
$Recent\_Tweets$	0.224***	0.508***	14.9***	0.385***	6.02**
$\log(Total\_Tweets)$	0.0668***	0.0053	8.60***	−0.0209	20.5***
$Size$	−0.0083	0.0814***	40.7***	0.133***	120***
ROA	−0.0313	−0.321**	1.42	−0.0683	0.0200
MB	0.0204**	0.0549***	7.68***	0.0525***	7.14***
$Debt$	−0.157***	−0.0905	0.530	−0.0365	2.37
$Volatility$	−0.321	−4.36***	3.93**	−1.49	0.380
$Cons$	−2.65***	−3.57***		−3.79***	
$Year\ FE$	Included	Included		Included	
$Month$ FE	Included	Included		Included	
$Industry\ FE$	Included	Included		Included	
N	48780	75082		75082	
Pseudo R2	0.0702	0.111		0.173	

Panel B, News classification based on cumulative abnormal return (CAR)

	(1) Other *probit*	(2) Before *probit*	$\Delta_{1,2}$ X^2	(3) After *probit*	$\Delta_{1,3}$ X^2
$Neu\_CAR_{(-1,+1)}$	-0.0862^{***}	-0.134^{***}	1.09	-0.187^{***}	6.11^{**}
$Neg\_CAR_{(-1,+1)}$	-0.0101	0.161^{***}	8.33^{***}	0.259^{***}	26.0^{***}
$Pos\_CAR_{(-1,+1)}$	-0.0464	0.0770^{*}	3.86^{**}	0.196^{***}	19.1^{***}
$Verified$	-0.0032	-0.0585	1.16	0.0604^{**}	1.92
$\log(Followers)$	0.0531^{***}	0.0392^{***}	0.800	0.0033	12.2^{***}
$\log(Friends)$	-0.0332^{***}	-0.0100	3.56^{*}	0.0294^{***}	31.2^{***}
$Recent\_Tweets$	0.198^{***}	0.473^{***}	13.8^{***}	0.335^{***}	4.35^{**}
$\log(Total\_Tweets)$	0.0708^{***}	0.0074	8.90^{***}	-0.0205	22.2^{***}
$Size$	-0.0145^{*}	0.0730^{***}	37.8^{***}	0.122^{***}	114^{***}
ROA	-0.0355	-0.388^{**}	2.02	-0.231^{*}	0.680
MB	0.0197^{**}	0.0592^{***}	9.76^{***}	0.0575^{***}	9.96^{***}
$Debt$	-0.167^{***}	-0.118^{*}	0.290	-0.0965^{*}	0.830
$Volatility$	-0.992	-6.26^{***}	6.13^{**}	-4.19^{***}	2.76^{*}
$Cons$	-2.44^{***}	-3.06^{***}		-2.92^{***}	
$Year\ FE$	Included	Included		Included	
$Month$ FE	Included	Included		Included	
$Industry\ FE$	Included	Included		Included	
N	47017	72420		72420	
Pseudo R2	0.0707	0.0749		0.0866	

Panel A examines news direction based on classifying Ravenpack articles, while Panel B uses a classification based on cumulative abnormal return (CAR). In each panel, regression (1) is run on the day-basis sample of firm-days with earnings announcements, 10-K filings, 10-Q filings, or 8-K filings, with at least 1 tweet and with no financial tweets during a six-hour window around centered on the event. Regressions (2) and (3) are run on the day-basis sample of firm-days with earnings announcements, 10-K filings, 10-Q filings, or 8-K filings and at least 1 tweet. Column $\Delta_{1,2}$ shows the difference between columns (1) and (2) using a X^2 test. Column $\Delta_{1,3}$ shows the difference between columns (1) and (3) using a X^2 test. Variable definitions for all variables are included in Appendix A. Methodology for Twitter topics is discussed in Appendix B.

Table 5: Tweet format

	(1) Financial *probit*	(2) Financial *probit*
$Earnings\_Ann$	0.479^{***}	0.364^{***}
$Form\_10\text{-}K, 10\text{-}Q$	0.0734^{***}	0.0496^{***}
$Form\_8\text{-}K$	0.0036	
$News\_Merger$		0.0607^{***}
$News\_Financial$		0.0783^{***}
$News\_MgmtForecast$		0.178^{***}
$News\_Exec$		0.0678^{***}
$News\_Analyst$		0.0110
$News\_ExecTrade$		-0.0014
$Verified$	-0.0059	0.0002
$\log(Followers)$	0.0740^{***}	0.0712^{***}
$\log(Friends)$	-0.0512^{***}	-0.0492^{***}
$Recent\_Tweets$	0.404^{***}	0.409^{***}
$\log(Total\_Tweets)$	0.0709^{***}	0.0691^{***}
$Size$	-0.0193^{***}	-0.0267^{***}
ROA	0.162^{***}	0.148^{***}
MB	0.0242^{***}	0.0231^{***}
$Debt$	-0.157^{***}	-0.151^{***}
$Volatility$	1.55^{***}	1.26^{***}
$Cons$	-2.89^{***}	-2.80^{***}
$Year\ FE$	Included	Included
$Month$ FE	Included	Included
$Industry\ FE$	Included	Included
N	805383	805383
Pseudo R2	0.106	0.108

All regressions are run on the day-basis sample restricted to firm-days with at least 1 tweet. The dependent variable for all regressions is $Format|Financial$, an indicator for if a financial tweet contained a link or media on a given day. Variable definitions for all variables are included in Appendix A. Methodology for Twitter topics is discussed in Appendix B, and methodology for news events is discussed in Appendix C.

Table 6: Format usage in financial tweets around major accounting events

Panel A, News classification based on Ravenpack

	(1) Non-filing/Ann Dates *probit*	(2) Earnings Ann *probit*	$\Delta_{1,2}$ X^2	(3) 10-K, 10-Q *probit*	$\Delta_{1,3}$ X^2	(4) 8-K Filing *probit*	$\Delta_{1,4}$ X^2
$Neu\_News\_Financial$	0.0970***	0.117***	0.180	0.0842	0.0600	0.161***	3.75*
$Neg\_News\_Financial$	0.0175	0.493***	122***	0.436***	83.7***	0.509***	174***
$Pos\_News\_Financial$	−0.0412*	0.456***	239***	0.434***	210***	0.500***	435***
$Verified$	−0.0117	−0.0201	0.0900	0.0128	0.600	0.0223	2.84*
$\log(Followers)$	0.0765***	0.0373***	18.5***	0.0468***	8.27***	0.0530***	13.1***
$\log(Friends)$	−0.0548***	−0.0174**	27.1***	−0.0179**	20.0***	−0.0353***	14.3***
$Recent\_Tweets$	0.494***	−0.0703*	174***	0.0967**	57.9***	0.168***	93.1***
$\log(Total\_Tweets)$	0.0904***	−0.0193	72.3***	0.0354**	14.8***	−0.0062	109***
$Size$	−0.0286***	0.0913***	210***	0.0118	18.5***	0.0138***	56.2***
ROA	0.215***	−0.223*	8.64***	0.0252	1.10	−0.242***	17.3***
MB	0.0209***	0.0526***	19.3***	0.0207**	0	0.0298***	2.66
$Debt$	−0.156***	−0.0522	4.55**	−0.192***	0.400	−0.134***	0.360
$Volatility$	1.86***	−2.19**	13.3***	−4.92***	34.0***	−0.639	13.5***
$Cons$	−3.10***	−2.24***		−1.85***		−2.09***	
$Year\ FE$	Included	Included		Included		Included	
$Month$ FE	Included	Included		Included		Included	
$Industry\ FE$	Included	Included		Included		Included	
N	660593	40037		38847		119014	
Pseudo R2	0.113	0.0760		0.0758		0.0825	

Panel B, News classification based on cumulative abnormal return (CAR)

	(1) Non-filing/Ann Dates	(2) Earnings Ann	$\Delta_{1,2}$	(3) 10-K, 10-Q	$\Delta_{1,3}$	(4) 8-K Filing	$\Delta_{1,4}$
	probit	*probit*	X^2	*probit*	X^2	*probit*	X^2
$Neu\_CAR_{(-1,+1)}$	-0.0191^{**}	-0.0585^{**}	2.13	-0.0887^{***}	5.25^{**}	-0.0878^{***}	13.2^{***}
$Neg\_CAR_{(-1,+1)}$	0.0009	0.0854^{***}	6.05^{**}	0.149^{***}	11.7^{***}	0.167^{***}	32.9^{***}
$Pos\_CAR_{(-1,+1)}$	0.0287	-0.0042	0.860	0.105^{**}	2.79^{*}	0.108^{***}	6.83^{***}
$Verified$	0.0022	-0.0245	0.870	0.0090	0.0500	0.0164	0.480
$\log(Followers)$	0.0784^{***}	0.0377^{***}	19.8^{***}	0.0483^{***}	8.67^{***}	0.0609^{***}	7.44^{***}
$\log(Friends)$	-0.0527^{***}	-0.0116^{*}	31.9^{***}	-0.0180^{**}	17.4^{***}	-0.0314^{***}	16.5^{***}
$Recent\_Tweets$	0.516^{***}	-0.110^{***}	210^{***}	0.0460	79.2^{***}	0.124^{***}	131^{***}
$\log(Total\_Tweets)$	0.0926^{***}	-0.0199	74.0^{***}	0.0357^{**}	15.4^{***}	-0.0071	114^{***}
$Size$	-0.0348^{***}	0.104^{***}	275^{***}	0.0072	19.1^{***}	0.0098^{**}	63.5^{***}
ROA	0.199^{***}	-0.260^{**}	9.54^{***}	-0.144	3.46^{*}	-0.221^{**}	14.0^{***}
MB	0.0204^{***}	0.0586^{***}	26.7^{***}	0.0226^{***}	0.0600	0.0326^{***}	4.95^{**}
$Debt$	-0.153^{***}	-0.0838^{*}	2.02	-0.221^{***}	1.38	-0.150^{***}	0.0100
$Volatility$	1.72^{***}	-1.57	8.69^{***}	-6.74^{***}	48.3^{***}	-1.33^{**}	19.3^{***}
$Cons$	-3.09^{***}	-2.01^{***}		-1.38^{***}		-1.84^{***}	
$Year\ FE$	Included	Included		Included		Included	
$Month$ FE	Included	Included		Included		Included	
$Industry\ FE$	Included	Included		Included		Included	
N	637486	38597		37492		114330	
Pseudo R2	0.118	0.0597		0.0617		0.0628	

Panel A examines news direction based on classifying Ravenpack articles, while Panel B uses a classification based on cumulative abnormal return (CAR). In each panel, regression (1) is run on the day-basis sample with tweets, excluding (-1,+1) firm-day windows with earnings announcements, 10-K filings, 10-Q filings, or 8-K filings; regression (2) is run on the day-basis sample restricted to (-1,+1) firm-day windows around earnings announcements with tweets; regression (3) is run on the day-basis sample restricted to (-1,+1) firm-day windows around 10-K or 10-Q filings with tweets; regression (4) is run on the day-basis sample restricted to (-1,+1) firm-day windows around 8-K filings with tweets. The dependent variable for all regressions is $Format|Financial$, an indicator for if a financial tweet contained a link or media on a given day. Column $\Delta_{1,2}$ shows the difference between columns (1) and (2) using a X^2 test. Column $\Delta_{1,3}$ shows the difference between columns (1) and (3) using a X^2 test. Column $\Delta_{1,4}$ shows the difference between columns (1) and (4) using a X^2 test. Variable definitions for all variables are included in Appendix A. Methodology for Twitter topics is discussed in Appendix B.

Table 7: Intraday format usage in financial tweets before and after major accounting events

Panel A, News classification based on Ravenpack

	(1) Other *probit*	(2) Before *probit*	$\Delta_{1,2}$ X^2	(3) After *probit*	$\Delta_{1,3}$ X^2
$Neu\_News\_Financial$	0.132**	0.283***	2.82*	0.512***	19.8***
$Neg\_News\_Financial$	0.156***	0.615***	54.6***	1.14***	283***
$Pos\_News\_Financial$	0.168***	0.601***	98.2***	1.07***	434***
$Verified$	−0.0337	−0.0303	0	0.0953***	6.66***
$\log(Followers)$	0.0593***	0.0363***	1.81	0.0070	10.3***
$\log(Friends)$	−0.0451***	−0.0123	6.21**	0.0230***	31.1***
$Recent\_Tweets$	0.329***	0.0813	8.46***	−0.177***	45.1***
$\log(Total\_Tweets)$	0.0289*	−0.0396*	8.59***	−0.0896***	28.9***
$Size$	−0.0202**	0.0706***	35.4***	0.129***	109***
ROA	−0.110	−0.543***	2.32	−0.240	0.220
MB	0.0176*	0.0496***	5.57**	0.0588***	9.90***
$Debt$	−0.119**	−0.0569	0.370	0.0285	2.96*
$Volatility$	−0.708	−5.08***	3.75*	−3.50**	2.01
$Cons$	−2.43***	−2.69***		−2.82***	
$Year\ FE$	Included	Included		Included	
$Month$ FE	Included	Included		Included	
$Industry\ FE$	Included	Included		Included	
N	48780	51343		51343	
Pseudo R2	0.0704	0.0885		0.175	

Panel B, News classification based on cumulative abnormal return (CAR)

	(1) Other *probit*	(2) Before *probit*	$\Delta_{1,2}$ X^2	(3) After *probit*	$\Delta_{1,3}$ X^2
$Neu\_CAR_{(-1,+1)}$	-0.0809^{**}	-0.129^{***}	0.930	-0.189^{***}	5.90^{**}
$Neg\_CAR_{(-1,+1)}$	0.0023	0.169^{***}	6.79^{***}	0.277^{***}	23.1^{***}
$Pos\_CAR_{(-1,+1)}$	-0.0509	0.0880^{*}	4.16^{**}	0.215^{***}	19.2^{***}
$Verified$	-0.0202	-0.0426	0.170	0.0556^{*}	2.34
$\log(Followers)$	0.0593^{***}	0.0459^{***}	0.620	0.0212^{*}	5.80^{**}
$\log(Friends)$	-0.0430^{***}	-0.0125	5.27^{**}	0.0277^{***}	33.4^{***}
$Recent\_Tweets$	0.309^{***}	0.0185	11.7^{***}	-0.253^{***}	56.3^{***}
$\log(Total\_Tweets)$	0.0332^{*}	-0.0421^{**}	10.0^{***}	-0.0908^{***}	31.9^{***}
$Size$	-0.0258^{***}	0.0638^{***}	33.8^{***}	0.118^{***}	106^{***}
ROA	-0.114	-0.587^{***}	2.63	-0.392^{**}	1.00
MB	0.0171^{*}	0.0541^{***}	7.18^{***}	0.0644^{***}	13.2^{***}
$Debt$	-0.125^{**}	-0.0748	0.250	-0.0354	1.13
$Volatility$	-1.52	-7.13^{***}	5.56^{**}	-6.57^{***}	6.53^{**}
$Cons$	-2.23^{***}	-2.18^{***}		-1.88^{***}	
$Year\ FE$	Included	Included		Included	
$Month$ FE	Included	Included		Included	
$Industry\ FE$	Included	Included		Included	
N	47017	49464		49464	
Pseudo R2	0.0702	0.0552		0.0887	

Panel A examines news direction based on classifying Ravenpack articles, while Panel B uses a classification based on cumulative abnormal return (CAR). In each panel, regression (1) is run on the day-basis sample of firm-days with earnings announcements, 10-K filings, 10-Q filings, or 8-K filings, with at least 1 tweet and with no financial tweets during a six-hour window around centered on the event. Regressions (2) and (3) are run on the day-basis sample of firm-days with earnings announcements, 10-K filings, 10-Q filings, or 8-K filings and at least 1 tweet. Column $\Delta_{1,2}$ shows the difference between columns (1) and (2) using a X^2 test. Column $\Delta_{1,3}$ shows the difference between columns (1) and (3) using a X^2 test. Variable definitions for all variables are included in Appendix A. Methodology for Twitter topics is discussed in Appendix B.

Table 8: Institutional ownership and tweeting

	Financial Tweets			Financial Tweet Format		
	(1) Low *logit*	(2) High *logit*	$\Delta_{1,2}$ X^2	(3) Low *logit*	(4) High *logit*	$\Delta_{3,4}$ X^2
$Earnings\_Ann$	0.545***	0.380***	39.2***	0.549***	0.392***	30.7***
$Form\_10\text{-}K, 10\text{-}Q$	0.0546***	0.104***	4.04**	0.0592***	0.108***	3.39*
$Form\_8\text{-}K$	−0.0109	0.0550***	13.2***	−0.0190	0.0407***	9.16***
$Verified$	0.0058	0.0087	0.0300	−0.0196	−0.0170	0.0200
$\log(Followers)$	0.0784***	0.0497***	30.8***	0.0977***	0.0572***	51.4***
$\log(Friends)$	−0.0436***	−0.0447***	0.0600	−0.0546***	−0.0502***	0.870
$Recent\_Tweets$	0.787***	1.04***	80.7***	0.308***	0.554***	47.7***
$\log(Total\_Tweets)$	0.143***	0.123***	7.42***	0.0822***	0.0652***	4.22**
$Size$	−0.0191***	0.0094**	31.7***	−0.0287***	0.0015	29.7***
ROA	0.373***	0.0156	15.4***	0.171***	−0.0838	7.15***
MB	0.0125***	0.0517***	96.5***	−0.0017	0.0550***	165***
$Debt$	−0.529***	0.0126	339***	−0.565***	0.0330*	336***
$Volatility$	1.88***	2.59***	1.71	1.79***	2.07***	0.220
$Cons$	−3.73***	−4.05***		−2.81***	−3.11***	
$Year\ FE$	Included	Included		Included	Included	
$Month$ FE	Included	Included		Included	Included	
$Industry\ FE$	Included	Included		Included	Included	
N	442173	440831		302371	281955	
Pseudo R2	0.171	0.155		0.121	0.0963	

Regression (1) is run on the day-basis sample restricted to firm-days with below median institutional ownership; regression (2) is run on the day-basis sample restricted to firm-days with above median institutional ownership; regression (3) is run on the day-basis sample restricted to firm-days with tweets and below median institutional ownership; regression (4) is run on the day-basis sample restricted to firm-days with tweets and above median institutional ownership. The dependent variable for regressions (1) and (2) is $FinancialTweets$, an indicator for if a company posted a financial tweet on a given trading day. The dependent variable for regressions (3) and (4) is $Format|Financial$, an indicator for if a financial tweet contained a link or media on a given day. Column $\Delta_{1,2}$ shows the difference between columns (1) and (2) using a X^2 test. Column $\Delta_{3,4}$ shows the difference between columns (3) and (4) using a X^2 test. Variable definitions for all variables are included in Appendix A. Methodology for Twitter topics is discussed in Appendix B.

Table 9: Feedback Effects on Tweeting

	Financial Tweets			Financial Tweet Format		
	(1)	(2)	(3)	(4)	(5)	(6)
	Earnings Ann	10-K, 10-Q	8-K Filing	Earnings Ann	10-K, 10-Q	8-K Filing
	logit	*logit*	*logit*	*logit*	*logit*	*logit*
$Feedback\_lag$	1.04***	0.864***	0.726***	0.853***	0.767***	0.656***
$Verified$	0.0964***	0.0824*	0.0373	0.0693*	0.0508	0.0271
$\log(Followers)$	−0.0086	0.0015	0.0251***	0.0090	0.0293*	0.0426***
$\log(Friends)$	0.0133	−0.0054	−0.0172***	0.0166	−0.0169	−0.0217***
$Recent\_Tweets$	0.539***	0.543***	0.597***	−0.0576	−0.0978	0.0329
$\log(Total\_Tweets)$	0.0244	0.0753***	0.0491***	−0.0490**	0.0246	−0.0242*
$Size$	0.184***	0.0606***	0.0539***	0.173***	0.0340**	0.0411***
ROA	−0.397**	−0.303	−0.0070	−0.558***	−0.606**	−0.139
MB	0.0686***	0.0280**	0.0407***	0.0737***	0.0283**	0.0417***
$Debt$	−0.0576	−0.325***	−0.134***	0.0052	−0.219**	−0.107**
$Volatility$	−3.18**	−8.43***	−1.30*	−2.47	−10.8***	−1.79**
$Cons$	−3.46***	−2.42***	−2.87***	−2.45***	−1.25***	−1.78***
$Year\ FE$	Included	Included	Included	Included	Included	Included
$Month$ FE	Included	Included	Included	Included	Included	Included
$Industry\ FE$	Included	Included	Included	Included	Included	Included
N	19458	19450	72151	13823	13078	49856
Pseudo R2	0.134	0.103	0.0895	0.100	0.0725	0.0578

Regressions (1) through (3) are run on the full day-basis sample. Regressions (4) through (6) are run on the full day-basis sample. The dependent variable for regressions (1) through (3) is $FinancialTweets$, an indicator for if a company posted a financial tweet on a given trading day. The dependent variable for regressions (4) through (6) is $FinancialTweets$, an indicator for if a company posted a financial tweet on a given trading day. Variable definitions for all variables are included in Appendix A. Methodology for Twitter topics is discussed in Appendix B.