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Discretionary Dissemination on Twitter

Abstract

Using a machine learning approach to analyze 12.8 million tweets posted by S&P 1500 firms from 2012 to 2016, we find that firms time financial tweets around earnings announcements, accounting filings as well as other important corporate events, and are more likely to use media (images or video) and links in those tweets. The above pattern holds for both good and bad news. Moreover, we find that feedback from Twitter users encourages future financial tweets and use of media and links. These results collectively suggest that firms make discretionary choices in timing and presentation format when disseminating information on social media and that they incorporate instantaneous feedback from Twitter users into their dissemination strategies.

***Keywords*:** Social media; discretionary dissemination; disclosures; Twitter; feedback.

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

Discretionary Dissemination 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, 2018) 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, 2018; Tang, 2018). Firms can choose strategically which information events to disseminate on social media and what format to use (plain text versus formatting tweets using hyperlinks or media attachments). Therefore, investors can acquire additional information or simply gain different perspectives on company-related issues by reading tweets disseminated 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 dissemination strategy is the equilibrium choice under dynamic interaction 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 and a Canadian scholar, 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. According to McLuhan's media theory in communication, investors may respond in different ways to the same information disseminated in different formats or through different media. A similar notion is also established in a variety of financial reporting and disclosure contexts in accounting research. Specifically, experimental studies have provided ample evidence that different presentation formats of equivalent information about a firm affect the valuations and trading behavior of analysts and investors (e.g., Hopkins, 1996; Hirst and Hopkins 1998; Dietrich, Kachelmeier, Kleinmuntz, and Linsmeier 2001; Bloomfield, Hodge, Hopkins, and Rennekamp 2015). Elliott, Hodge, and Sedor (2012) use an experiment to provide supporting evidence that using online video to accompany press releases about restatements affects investors' investment decisions. If managers understand the implications of different presentation formats for information processing among investors, they will use discretion when disseminating information. The purpose of our study is thus to explore what types of corporate events will trigger firms to disseminate information on Twitter and the associated timing and format of that dissemination.[1]

Compared with other communication channels, Twitter is unique in many dimensions. It has a strict character limit for each tweet, so the message must be simple, short, and concise. Firms can bypass the limit by including multimedia such as hyperlinks, images, and videos, giving receivers the option to read further. Twitter enables firms to initiate direct communication with a

[1] Some studies use the word 'dissemination' specifically for information already disclosed elsewhere (e.g., Jung et al., 2018). Firms directly disseminate information to their Twitter followers. Such information often overlaps with that disclosed on company websites, the SEC's EDGAR website, or through other channels. In April 2013, the SEC issued a guidance confirming that companies can use social media to announce key information in compliance with Regulation Fair Disclosure (Regulation FD) as long as investors are alerted about which social media will be used to disseminate such information. Throughout our paper, we use the term "dissemination" with a broad definition, i.e., it consists of both disclosure of new information and dissemination of news already disclosed elsewhere. In an additional test, we examine the difference in disclosure decision before and after April 2013.

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. In contrast to a pull information system, where the request for the transmission of information is initiated by the recipients, the push technology of social media allows firms to send information directly to the recipients, therefore significantly reducing the information search and processing costs and increasing the speed of communication. More importantly, by monitoring investors' reactions to tweets continuously via the functions of likes, retweets, replies, etc., firms can adjust their dissemination decisions dynamically.

Using a complete 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 hypothesis investigates whether firms choose the timing of financial disclosures on Twitter to coincide with earnings announcements, SEC filings, and other corporate events and whether their tweeting activities depend on the direction of news events (positive or negative). The second hypothesis examines the presentation format of tweets around these major corporate events based on the premise that firms will use the unique features of Twitter to enhance their dissemination.[2] We refer to tweets that contain hyperlinks, images or videos as 'tweets with formatting' (or 'formatted tweets') as opposed to tweets with plain text only. In the third hypothesis, we examine whether

[2] Intuitively, we argue that some presentation formats make the information easier to process than other format. For instance, a short video about the company's key performance metrics makes the information visual and easier to understand than a lengthy annual or quarterly report. Although we do not expect investors to replace reading accounting reports with reading tweets, it is reasonable to expect that investors can find interpretation of, and different perspectives on, company information on their Twitter accounts. It is interesting to note that early research in human information processing (for example, Johnson, Payne, and Bettman 1988) finds that presentation of probabilities in a more complex looking, hard-to-process fractional format (e.g., 456/570) results in significantly more preference reversals than presentation of probabilities in an easier-to-process decimal format (e.g., .8). This lends further support to our intuition about why presentation format of tweets matters.

firms respond to feedback on their tweets by investigating firms' future level of tweeting activities and future use of presentation format.

We conjecture that firms will tweet more 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 will have less incentive to tweet. Following this line of reasoning, we predict that firms choose when and what to post on Twitter to coincide with corporate events with a clear news direction. We use a machine learning algorithm to examine the content of each company-generated tweet and to classify it into one of the following categories: business, marketing, and other tweets. Because our primary focus is on tweets containing financial content, we further classify business-related tweets into financial and non-financial tweet categories. We find that firms increase tweeting and specifically increase the dissemination of financial tweets around earnings announcements as well as quarterly and annual report filings. A similar tweeting pattern is observed around announcements of mergers and acquisition, financial news, management forecasts, and executive information. We find this pattern is pronounced around earnings announcements, annual and quarterly reports, and 8-K filings when the events have a clear positive or negative direction. Furthermore, we find that firms are more likely to post a formatted tweet (i.e., tweets containing media or a link) around corporate events with a clear positive or negative direction. Collectively, the evidence suggests that firms make discretionary choices when tweeting.

We then test whether the discretionary choice of timing and the format of tweets is conditional upon the feedback provided by Twitter users. Investors sometimes neglect relevant aspects of the information that is publicly disclosed due to limited capacity and resources in processing information (Merton, 1987; Hong and Stein, 1999; Hirshleifer and Teoh, 2003). We predict that feedback influences firms' incentives in communicating financial information to their Twitter followers. We use feedback indicators, i.e., whether a financial tweet received likes or retweets, as a proxy for feedback effect, and we find that feedback affects firms' future tweeting behavior, encouraging more financial tweets and use of formatting.[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 a machine learning algorithm to classify a large volume of tweets (12.8 million) into financial and non-financial tweets. The advantage of this approach is that it improves classification precision over a dictionary approach while offering a more researcher-bias-free assessment of the content of the examined tweets.[4] We highlight that firms strategically select the types of event and timing to disseminate financial information on Twitter.

Second, our study is the first large sample archival study showing that media and hyperlinks are included in tweets discretionarily and that the decision varies with both the type of news event and the direction of the news. Experimental studies in accounting suggest the importance of presentation format in conveying information, for example, Elliott, Hodge, and Sedor (2012) show that using online video to announce and explain restatements could significantly influence trust from investors and consequently affect their investment decisions.

[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 active consumers…because Twitter…helps you identify things that people care about."
[4] Specifically, our methodology uses a Bayesian algorithm to learn a set of topics discussed across documents. The only researcher interaction with the algorithm is in determining the algorithm's hyperparameters and the labeling of topics. The algorithm alone determines the words within a topic and their weights. A dictionary approach requires researcher interaction for the selecting of each individual word (and optionally, its weighting).

Few archival studies examine the strategic choice of presentation format. The current literature on corporate use of social media largely does not consider presentation format, either, partly due to the data limitations and challenges of content analyses. An exception is Blankespoor et al. (2014), who find that including links in tweets around earnings announcements increases liquidity. However, they document no strategic use of links by firms conditional on earnings direction or magnitude. Their sample consists of high technology firms and the size of the sample is small. We extend their study by providing new evidence that firms are more likely to use links and media (images and video) in tweets around news events when the news is good or bad. Thus, our study adds to the understanding of how firms use Twitter and its embedded functions effectively to manage information flow to the capital market.

Moreover, Twitter allows users to provide feedback on tweets through likes, retweets, or replies. This feature is not available through traditional disclosure channels like SEC filings. We show that firms learn from feedback on Twitter and adjust their dissemination practices accordingly. Bond, Edmans, and Goldstein (2012) suggest that the market provides information back to managers, and that managers respond through real actions, highlighting the importance of incorporating such feedback effects when studying managers' decisions. While evidence on feedback effects is rapidly accumulating (e.g., Bakke and Whited, 2010; Foucault and Fresard, 2014; Bai Philippon, and Savov, 2016; Jayaraman and Wu 2018), direct empirical evidence is rare, as the process of learning from price is noisy. Our study examines the opinion provided by Twitter followers and thus provides direct evidence of a dynamic feedback effect on the equilibrium outcome of information dissemination which prior research was unable to address using disclosure data on other platforms.

Finally, our study complements the work of Jung et al. (2018), who find that firms *avoid* disseminating news on Twitter when the news is bad and when the magnitude of the bad news is worse. In contrast to Jung et al. (2018), we show that firms are likely to disseminate both good and bad financial news on Twitter and that the pattern is independent of litigation risk.[5] The new insight on firms' *symmetric* treatment of bad versus good news is surprising yet reasonable. On one hand, if the negative news event has been disclosed elsewhere, the incentives to avoid tweeting about it should be minimal. On the other hand, if the negative news event has not been disclosed elsewhere, prior studies (such as Lee et al. 2015) show that the interactive feature of social media makes it a reasonable outlet for firms to break the news and provide explanations or justifications for poor performance.

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

2. Literature Review and Hypothesis Development

2.1 Literature review

The difference between information disclosure and dissemination is subtle. Disclosure often refers to the release of new information, while discretionary dissemination refers to a firm's decision on whether to release new or existing firm-specific information through a specific channel. Discretionary disclosure has been widely studied in accounting (see, e.g., Fields, Lys, and Vincent, 2001; Healy and Palepu, 2001; Beyer, Cohen, Lys, and Walther, 2010; Leuz and Wysocki, 2016). For example, a number of studies on conference calls examine management's strategic communication and its association with information content (Hollander, Pronk, Roelofsen, 2010),

[5] We conduct further analysis to reconcile between the two studies. The details are discussed in subsection 5.1.

firm performance (Mayew and Venkatachalam, 2012), financial fraud, and misreporting (Hobson, Mayew, and Venkatachalam, 2012; Larcker and Zakolyukina, 2012). On the other hand, strategic information dissemination is relatively new. Prior research on disclosure largely focuses on conventional communication channels. In recent years, social media platforms, as unique and interactive information dissemination platforms, have been attracting not only more usage by companies but also more interest from researchers.

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) find that corporate social media attenuates the negative price reaction to recall announcements. Miller and Skinner (2015) discuss 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. (2018) and Tang (2018) 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 firm-specific 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. (2018) 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. Crowley, Huang, Lu, and Luo (2018) document that firms with lower CSR scores post more tweets on their CSR activities, supporting strategic dissemination following a green-washing strategy.

Our study adds to the literature by focusing on the *timing* and *presentation format* of company-initiated tweets in connection with significant corporate events and by showing how the decision to disseminate information on social media varies with the feedback from Twitter followers. Moreover, ours is the first study in accounting to use machine learning algorithms to process a large volume of tweets (12.8 million) in order to study the dissemination of financial news on social media and the first large sample archival study showing the discretionary use of presentation format of information. It provides a unique perspective on corporate use of social media as an innovative information channel with instantaneous and continuous feedback.

2.2 Hypotheses development

Twitter provides a quick means of conveying information to investors. Firms can bypass the 140-character constraint by embedding hyperlinks, images, and videos.[6] Twitter allows firms to initiate communication with followers directly; this feature significantly reduces communication and investor search costs compared with 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 dissemination 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 what and how to disseminate 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 increasing firm visibility by attracting more followers.[7] Therefore, we expect firms to be

[6] Starting from November 2017, Twitter has doubled the character limit to 280 in an effort to make expression easier.
[7] The marketing literature has documented users' motivations to contribute content to Twitter and has 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).

proactive in disclosing events over which they have full control. Classifying 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 significant corporate events such as earnings announcements with material information content and 8-K filings with the SEC.

To the extent that information dissemination is a voluntary practice, firms' incentives for dissemination largely overlap with their incentives for voluntary disclosure, therefore, we draw on findings in the prior literature to motivate our hypotheses. The literature on voluntary disclosure suggests that firms disclose differently depending on the direction of the news available to the capital market, the evidence on how firms disclose positive versus negative news is mixed. Different assumptions and settings in theoretical models may lead to different predictions. Under 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 provide mixed evidence. 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). 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 hypothesis is thus stated as follows:

Hypothesis 1*: Firms choose the timing of financial disclosures on Twitter in connection with significant news events (regardless of whether the news is positive or negative).*

The purpose of testing this hypothesis is to provide descriptive evidence on companies' likelihood of tweeting financial information and the timing of company tweets in relation to earnings announcements, SEC filings (10-K, 10-Q, and 8-K), as well as other significant corporate events. It is worth noting that this hypothesis is not without tension. Ex ante, it is unclear whether firms will post financial tweets strategically. Earlier Twitter adopters use social media primarily for marketing purposes to communicate with their customers. After Twitter became more popular, firms may have adjusted their usage of the platform to include communicating financial implications of corporate events to their current or potential investors, particularly after the SEC began allowing firms to disclose new information on social media in April 2013. Moreover, our conjecture that firms' dissemination decision is independent of news direction arises from two co-existing views. One the one hand, many conventional studies on strategic disclosure suggest that firms have various incentives to depress bad news. When extending to social media, it is likely that firms will adopt a consistent disclosure strategy and continue to disclose good news while withholding bad news, particularly when social media amplifies the messages broadcasted, whether good or bad. On the other hand, as discussed above, managers are also under pressure to make timely disclosure of bad news to deter competition or mitigate litigation risk. Furthermore, the interactive feature of social media makes it a useful channel to provide explanations and justifications to investors to mitigate the negative impact of bad news. Based on these arguments, we predict that firms will disseminate information on Twitter whenever the news contains material information content, good or bad, that will potentially affect investors' perception of the firms.

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 or clarify the 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. Experimental studies in accounting have shown that presentation format has additional influence over the effect of information content. We thus present our second hypothesis:

> ***Hypothesis 2:*** *Firms choose presentation format (whether tweets are plain text only or include images, videos, and hyperlinks) on Twitter in connection with significant news events (regardless of whether the news is 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, due to the data limitations and challenges of content analyses, no prior 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 that firms give to events and that firms take advantage of the unique features discussed earlier. Similar to our prediction on tweet timing, we expect firms to be more likely to use images, videos, and hyperlinks in financial tweets to enhance information dissemination whenever the news has a clear positive or negative direction.

Our third hypothesis investigates the relationship between feedback and the choice of timing and formatting in 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. 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 those investors who have limited resources or skills needed to search for information about firm fundamentals or the stock market in the traditional 'pull' information system. Indeed, over 80% of Twitter users access their accounts via mobile devices, allowing for users to quickly receive information that is disseminated to them. If investors find Twitter to be useful as a source of information, investors can easily provide feedback directly on Twitter. The feedback effect of capital markets on manager's actions has been explored in recent studies (e.g., Bakke and Whited, 2010; Foucault and Fresard, 2014; Bai Philippon, and Savov, 2016; Jayaraman and Wu 2018), but the evidence supporting the feedback effect is indirect. Dye and Sridhar (2002) theoretically show that disclosures lead to market responses which in turn provide valuable feedback to the manager. Based on these works, we expect firms value the feedback from Twitter followers and alter their dissemination strategy in the future. We thus state the third hypothesis as follows:

> ***Hypothesis 3****: Firms receiving feedback on their tweets are more likely to tweet more in the future and to choose timing and formatting to coincide with significant news events.*

Interesting and engaging tweets would generate strong feedback and information disseminated via social media could be more timely and useful. Consequently, firms may respond to feedback. We test Hypothesis 3 by examining the likelihood of future tweeting activities for firms receiving feedback and the variance of tweet timing and format around news events against an indicator of past feedback. We expect firms to respond to the feedback on tweets around significant accounting events like earnings announcements. Our intuition is that earnings announcements and SEC filings are of first-order importance to retail investors. While sophisticated investors likely obtain such information elsewhere—from press releases, conference calls, analysts, or SEC filings—firms can use Twitter to disseminate key information quickly and reach more retail investors. Firms can also include hyperlinks to direct investors to read earnings reports on their websites, or they can use images and videos to highlight key statistics of their financial performance and future prospect. Therefore, we expect firms receiving feedback to tweet more and to make more use of formatting features when tweeting around financial news in the future.

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 handles, we identify the Twitter IDs associated with the accounts via the Twitter API 2.0. 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 Twitter accounts for 1,433 firms. Among the S&P 1500 firms in our sample period, 383 firms have no Twitter accounts, 302 firms adopt Twitter during our sample period, and 1,141 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 240 have adopted Twitter during the sample period and 975 have an account throughout.

To obtain companies' tweets, we used the 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 these two data sources 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 Fundamentals Annual and CRSP, respectively. Earnings announcement dates and times come from Compustat Fundamentals Quarterly 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. 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) complete information for 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, 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.[8] 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, and as media generally co-occurs with a link in our sample (over 80% of the time at the day level; over 75% at the individual tweet level), 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.

[8] We chose 60 topics by running topic models with varying numbers of topics from 50 to 100, optimizing for the clarity of the financial topic. The optimal number of topics in this process was 60.

Our feedback measure used in testing the third hypothesis, *Feedback_lag*, is an indicator variable equal to 1 when a financial tweet received a like or a retweet on the prior event of the same type which included a financial tweet, and 0 otherwise.[9]

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.'[10] We also include measures to capture the number of 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 are as of the time the data was collected, 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 Fundamentals 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 (to the minute) of release of earnings announcements. Due to data availability in I/B/E/S, our intraday tests have significantly fewer events 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

[9] We do not include replies as they are not tracked or included in data from the Twitter API or GNIP.
[10] For more information about verified accounts, see: https://twitter.com/verified.

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 filter 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*). These six news events cover 68% of all 8-K filing firm-date pairs in our sample. We further classify financial news as positive (negative) if the news is indicative of earnings or sales increasing (decreasing). This classification is based on the topic of the article rather than its sentiment. A full description of the components of each category and the decomposition of financial news into positive and negative 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 ($Pos\_News_{(-1,+1)}$) and negative news ($Neg\_News_{(-1,+1)}$). 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 and is not our focus.

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 news 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 Other measures

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)

To investigate H1 on tweet timing, we construct a daily dataset of the measures described in Section 3.2. We use logistic regression to examine the impact of various events on firms' daily tweeting behavior, as given by equation (1).

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

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 variables 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) two indicators showing whether the financial news is positive or negative; and (4) two indicators showing whether abnormal returns around the trading day are positive or negative. As the indicators for negative and positive news are interactions between our news events and our news sign measures, we also check marginal effects for all such coefficients. All coefficients' marginal effects are consistent with the coefficient signs, as is detailed in Section 5.2.

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 information technology, are more likely to tweet in general). For industry fixed effects, we use GICS sector.

For intraday tests, we examine 24-hour periods around announcements, (–12, +12) hours, using a firm-hour sample. We follow equation (1), including the firm-, year-, and month- fixed effects, but use a more restrictive definition for the dependent variable and the event indicators. Our dependent variable is equal to one only if there is a financial tweet by the firm in a given hour. We present our results using event indicators equal to one only for the 3 hours before and after the event occurred, (–3, +3) hours. We also add an additional fixed effect to this model: the time at the NYSE. As the number of financial tweets varies significantly by hour within the day, this hour-at-NYSE fixed effect controls for any natural variation in tweets due to the time of day (see Figure 1, Panel B). For robustness, we also test event windows of (–2, +2) and (–1, +1) hours, finding qualitatively similar results.

4.1.2 Format test (H2)

We use logistic 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.

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

In equation (2) (where *i* represents firms and *d* represents trading days), the dependent variable is *Format*|*Financial*. We examine two specific formatting decisions: whether a firm includes images or videos 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 one during certain periods around these events.

We replicate the above test using the same intraday framework as used for our timing tests. We use the same regression structure as the intraday tests for timing, including the industry, year, month, and hour-at-NYSE fixed effects, but require the 24-hour period to have at least one tweet. Our dependent variable is equal to one only if there is a financial tweet including either media or a link in the hour by the firm. We use event indicators equal to one only for the 3 hours before and after the event occurred, (–3, +3) hours. For robustness, we replicate our tests using (–2, +2) and (–1, +1) hour event indicators, finding qualitatively similar results.

4.1.3 Feedback test (H3)

We use both equations (1) and (2) to examine how the discretionary choice of timing and format of future tweets are affected by the feedback firms receive from their Twitter followers. We include a measure of lagged feedback within accounting event to account for Twitter users' prior reaction to the firms' financial information dissemination on Twitter. We calculate the measure separately for earnings announcements, 10-K/10-Q filings, and 8-K filings. We expect feedback from Twitter users to have a positive influence on timing and formatting on Twitter.

4.2 Results

4.2.1 Univariate Statistics

Table 1 presents the summary statistics of our daily measures. The sample consists of 1,229,734 daily observations, where 65.5% of firm-days involve at least one tweet, and 3.38% of firm-days involve a financial tweet. 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 financial news and M&A news.

Regarding the content of firm tweets, untabulated results show that firms tweet business-related tweets on 29.5% of days. When examining subtopics of business tweets, 3.38% of firm-days (11.5% of firm-days with business tweets) involve a financial tweet, which are the tweets our analysis focuses on. Regarding other tweet types, we find that firms tweet marketing related content on 58.5% of firm-days, including tweets about customer support (18.4% of firm-days), tweets about conferences or tradeshows (44.4% of firm-days), or tweets about other marketing related content (41.4% of firm-days). In addition, firms tweet content that is not related to business or marketing on 32.1% of firm days. Overall, there is a large amount of overlap over the type of content posted on each day, as firms post an average of 10.4 tweets per day.

Verified Twitter accounts tend to be older and represent 28.2% of total observations.[11] 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 is 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.[12]

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

[11] It is unclear whether or not these accounts are not verified because firms did not consider verification as value-added and did not seek verification.
[12] Correlation matrices are reported in Table A1 of the online appendix.

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.

4.2.2. Determinants of adopting Twitter

The S&P 1500 firms in our sample period are comprised of 1,639 firms (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 accounts. We first explore the factors driving the decision to create a company Twitter account and to use it to send at least one tweet. It is potentially important to control for these factors in our disclosure regressions. We run a logistic model with a set of firm specific financial variables as controls, and include year, month, and industry fixed effects. The results are presented in Table 2. We find that size and market-to-book ratio are significantly positively 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. Examining the trend in year fixed effects (using χ^2 tests, untabulated), we find a statistically significant increase in the number of firms that have joined Twitter each year from 2013 through 2015, with no significant difference between year 2015 and 2016. This implies that the growth of firms on Twitter began to level off in 2016. Examining the industry fixed effects, we find that firms in the Communication Services, Information Technology, and Consumer Discretionary industries (GICS codes 50, 45, and 25, respectively) are significantly more likely to adopt Twitter than all other industries. This observation is consistent with the assertion that IT firms tend to be early adopters of technology (Blankespoor et al. 2014). Consumer Discretionary firms are in sub-industries that are consumer facing and more marketing oriented, including sub-industries such as consumer electronics, apparel, and retail stores.[13]

4.2.3 Timing tests (H1)

We use daily windows to test firms' timing of tweets. The regressions testing Hypothesis 1 are presented in Tables 3 and 4. Table 3 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 1. For 8-K filings, we do not find a higher likelihood of financial tweets. However, replacing 8-K filings with a vector of six news events, we find a higher likelihood of financial tweets around M&A, financial information, management forecasts, and executive news, all of which tend to be events that are either initiated by or controlled by the firms.

Table 4 further presents the impact of major accounting events on tweeting behavior, including indicators of significantly positive or negative events. We have two indicator variables, $Neg\_News_{(-1,+1)}$ and $Pos\_News_{(-1,+1)}$, each indicator variable is interacted with earnings announcements, annual and quarterly reports, and 8-K filing, respectively. The value of these indicators is 0 when there is no event during the day and 1 when there is a significantly negative or positive earnings announcement, 10-K/10-Q filing, or 8-K filing. Hypothesis 1 predicts that tweets are concentrated around significantly positive and negative news. Columns 1, 2, and 3 of Table 4, Panel A presents firms' tweeting behavior around earnings announcements, 10-K/10-Q filings, and 8-K filings when using RavenPack to classify the direction of news. The significantly

[13] The logistic model detailed in the text is based on fiscal year end dates. We find identical results for important control variables and industries using (1) calendar year end dates, (2) a monthly logistic regression instead of yearly logistic regression, and (3) a Cox proportional hazards model modeling the time to adopt a Twitter account (in days from Jan 3, 2012, the first trading day in our sample).

positive coefficients on $Neg\_News_{(-1,+1)}$ and $Pos\_News_{(-1,+1)}$ suggest that firms are more likely to post financial tweets around both positive and negative news for all these corporate events ($p < 0.01$ for all coefficients). These results support Hypothesis 1. Next, we extend the above analysis using market reaction to classify the direction of news. The results are presented in Panel B of Table 4. The coefficients on $Neg\_News_{(-1,+1)}$ and $Pos\_News_{(-1,+1)}$, show that the likelihood of posting financial tweets increase for all positive and negative accounting events. The check using alternative news classification provides additional support for Hypothesis 1 — that is, in general, firms post financial tweets around the time when positive or negative news becomes public.

The above evidence is partially different from the findings in Jung et al. (2018), which shows that managers are less likely to disseminate bad news in the settings of earnings announcements. We show that managers are equally likely to disseminate both good and bad news on Twitters as far as news event contains material information. We will further explore the differences in Section 5.1.

4.2.4 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 show 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).[14]

The logistic regression testing Hypothesis 2 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 2. Financial tweets with format do not

[14] This number is comparable to that reported in Blankespoor et al. (2014), who examine a much smaller set of firms (82 IT firms) and find that, on average, 75.4% of tweets in their sample contain hyperlinks.

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 M&A, financial information, management forecasts, and executive news.

Table 6 shows how format use in financial tweets is related to the sign of financial news around major corporate events. Panel A presents the results from news classification based on RavenPack. The significantly positive coefficients on $Neg\_News_{(-1,+1)}$ and $Pos\_News_{(-1,+1)}$ suggest that firms are more likely to choose to use format in financial tweets around both positive and negative news for all these corporate events ($p<0.01$ for all coefficients). These results are consistent with Hypothesis 2, showing that both significantly positive and negative news increase the likelihood of including media or links in financial tweets. The coefficients on many other control variables are significant and consistent with prior expectations. Panel B repeats the above analysis using cumulative abnormal returns (CAR) to classify news. All three columns show a very similar pattern: The likelihood of format use in financial tweets increases around earnings announcements, 10-K/10-Q filings, and 8-K filings with both positive and negative news. Taken together, these results support Hypothesis 2 that firms are more likely to use media and links in financial tweets around corporate events when news is significant.

4.2.5 Intraday analysis supporting H1 and H2

We examine the intraday timing of tweets to seek additional support for our hypotheses. Panels A and B of Table 7, present select univariate statistics on the percent of hours with financial tweets and formatted financial tweets within 3 hours of the events versus between 3 and 12 hours from the events. In Panel A, we see that firms tweet significantly more frequently within 3 hours of earnings announcements, 10-K/10-Q filings, and 8-K filings as compared to between 3 and 12 hours from the events ($p<0.01$ for all comparisons). Panel B shows a similar pattern for format usage, with a greater proportion of formatted financial tweets within 3 hours of the events.

Table 8, Panel A, presents the intraday timing of financial tweets around earnings announcements, annual and quarterly reports, and 8-K filings. We find that, within the 3 hours before and after earnings announcements, 10-K/10-Q filings, and 8-K filings, there is a significant increase in firms posting financial tweets on Twitter ($p<0.01$ for all coefficients). In robustness checks, we find qualitatively similar results using hourly windows of (–2, +2) and (–1, +1). These results indicate further support for Hypothesis 1, that firms time their financial tweets within the day in conjunction with their other disclosures.

In Table 8, Panel B, we present the intraday financial tweet format results for earnings announcements, 10-K/10-Q filings, and 8-K filings. We find a significant increase in the use of links and media in financial tweets around all three event types ($p<0.01$ for all coefficients). In robustness checks, we find qualitatively similar results on (–2, +2) and (–1, +1) windows. These results indicate further support for Hypothesis 2, that firms choose the format of their financial tweets in conjunction with news events.

4.2.6 Feedback tests (H3)

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 any of the three methods, Twitter followers can show that they pay attention to a company's tweets.

To test the feedback hypothesis, H3, we aggregate two of the three feedback methods (likes and retweets) into a binary measure, *Feedback_lag*, equal to 1 when at least one method was used in response to a past event of the same type which included a financial tweet, and 0 otherwise. We explicitly examine whether feedback affects firms' subsequent disclosure behavior, shedding light on whether opinions from Twitter followers can affect disclosure behavior in the future.

Univariate statistics for *Feedback_lag* are presented in Table 7, Panel C. We find that earnings announcements are the most likely event to have received feedback, with 1.6% of earnings announcements with financial tweets receiving feedback on Twitter. Table 7, Panel D presents univariate evidence of the effect of feedback on firms' dissemination of financial information on Twitter. Around earnings announcements, firms that previously tweeted financial information around an earnings announcement have a baseline 7% probability of tweeting again. However, if the firm received feedback on their previous tweet, they have a 41.4% probability of tweeting, approximately 490% higher than the baseline probability without receiving feedback. We find similar patterns for 10-K/10-Q filings and 8-K filings when firms received prior feedback, with increases of 420% and 220% over their respective baselines. In Table 7, Panel E, we find a similar pattern for usage of formatting in financial tweets after receiving feedback, with increases of approximately 390%, 360%, and 190% for earnings announcements, 10-K/10-Q filings, and SEC filings, respectively.

We test for each event type to determine whether feedback around a previous event influences the likelihood of a firm providing a financial tweet around an event of the same type, and whether feedback influences firms to use formatting within financial tweets around events conditional on having tweeted around the events. Panels A and B of Table 9 show the results for timing and format tests, respectively. We find that feedback on financial tweets around earnings announcements, 10-K/10-Q filings, and 8-K filings all reinforce firms' tweeting 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 the opinion from Twitter followers does lead firms to adopt a more proactive disclosure strategy on Twitter.

5. Robustness Checks

5.1 Strategic dissemination on good and bad news

We find that managers are more likely to post financial tweets around the time of significant accounting events such as earnings announcements regardless of whether news events are negative or positive. Our findings differ from those in Jung et al. (2018), who suggest that firms are less likely to disseminate news when earnings news is negative. We conduct a battery of tests to reconcile the seemingly puzzling divergence between the two studies as a part of scientific inquiry. Whether firms respond to good and bad news differently has always been an important research question in accounting. We summarize the results below and provide the details of our tests in the online appendix tables.

We notice several significant visible differences between two studies. First, the time period and size of our sample are quite different. The sample of Jung et al. (2018) consists of tweets from the first quarter of 2010 through 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.

Their sample only consists of 2,273 earnings related tweets over 2,273 firm-quarters.[15] Our sample consists of 12.8 million tweets from 1,215 S&P 1500 firms in the period from January 2012 through December 2016. Our sample has 59,114 financial tweets over 41,571 firm-days. Second, Jung et al. (2018) 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 detailed in footnote 7 of Jung et al. (2018) to identify earnings-related tweets. Third, Jung et al. (2018) use earnings surprise to classify good or bad news as they focus solely on earnings news, while we use both RavenPack and $CAR_{(-1,1)}$ to classify good or bad news for a comprehensive set of accounting filings and corporate events.

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 Twitter 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 disclosure 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 embracing companies' use of social media. 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.

We focus on the effect of the second difference in this reconciliation test. We conduct all our primary tests presented above using a dictionary approach. We first examine the agreement between the machine-learning-based LDA approach and dictionary approach. Panel B of Table A2 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

[15] 2,273 is the number backed out from Table 1, Panel D of Jung et al (2018), which is also consistent with the number of quarters reported in Panel B.

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 generates higher percentages of tweets around these events despite classifying fewer tweets as financial tweets, again suggesting that the LDA approach is more powerful than a dictionary approach.

Next, we reclassify the financial tweets using the dictionary approach and repeat all the tests in the paper. Table A3 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 follow the sample cuts discussed in Jung et al. (2018), examining litigation, then the number of retail investors, and the number of Twitter followers. 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 A4), contradicting the findings in Jung et al. (2018). This finding is robust to news measured by RavenPack (Panel A of Table A4).

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. Intuitively, our finding should not be considered as a complete surprise. If negative news events have been disclosed elsewhere, the incentives to avoid disseminating the information on a prominent social media outlet such as Twitter should be minimal. On the other hand, if the negative news event had not been disclosed elsewhere, the interactive features of social media would make it a reasonable outlet for firms to break the news and provide explanations or justifications for poor performance.

5.2 Other Robustness Checks

SEC ruling in 2013: The SEC ruling in April 2013 may affect the propensity of firms to disclose new information on Twitter. Without clear guidance before April 2013, firms may avoid disclosing new information on social media, instead disseminating information already disclosed elsewhere. The SEC's guidance clarifies the legal burden of disclosure on Twitter, making it clear that new information could be disclosed on Twitter first. To examine the impact of the new rule, we split our sample into post- and pre-SEC ruling periods with respect to April 2013 (while removing this month from our data). The robustness check on Tables 3 to 6 and Table 9 validates our main results under both current and prior social media disclosure regimes. In the pre-SEC-ruling period, however, we do find somewhat weaker results in our format tests, with only earnings announcements driving financial tweet formatting.

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 robust, but weaker for earnings announcements, particularly around negative news earnings announcement released during trading hours (which represent only 0.36% of all earnings announcement in our sample).

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 Twitter 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 for our windowed timing and format tests and our feedback tests when we: (1) remove the 11 firms with an IR Twitter account, (2) restrict our sample to the 862 firms that link their IR website to their main Twitter account, and (3) restrict 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 affects 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 Twitter account creation: To control for potential endogeneity due to firms joining Twitter at different times, we retest our results after removing the 240 firms from our main sample that joined after our sample start date of January 1, 2012. We find that results are inferentially similar in testing firm timing, format, and feedback.

Econometric concerns: As some of the indicators we used in logistic regressions are interactions between multiple variables, such as $Neg\_News_{(-1,+1)}$ being interacted with our *Event* indicators, we also teste the marginal effects, as in Norton, Wang, and Ai (2004), for all such variables of interest across all regressions in tables. All significant coefficients in the tables have consistent and significant marginal effects at $p<0.05$.

6. Conclusions

This paper examines whether firms make discretionary choices regarding the timing and presentation format used when they disseminate news on Twitter. Using a large sample of tweets generated by S&P 1500 firms, we find that firms' tweet timing is positively associated with major accounting events regardless whether the news is positive or negative. This result is in contrast to prior research, which shows that managers disclose bad and good news on social media differently. We also find 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 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 receiving feedback on Twitter will post more financial tweets and include more media and links around future earnings announcements, 10-K, 10-Q, and 8-K filings. Use of the feedback feature on Twitter appears to affect firms' information dissemination behavior dynamically and leads them to be more proactive in using Twitter to enhance their disclosures in the future.

Our study is the first large sample study to document firms' discretionary dissemination choices on Twitter around a diverse set of information events and accounting filings. Our evidence suggests that managers exercise discretion regarding the timing and presentation format 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 bring 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.

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Appendix A. Variable Definitions

Variable Name	Definition
Dependent Variables	
FinancialTweets	An indicator equal to 1 if at least one of the company's tweets discusses financial information on a given day, 0 otherwise.
Format|Financial	An indicator equal to 1 if a financial tweet by a company on a given day contains media or a hyperlink.
$FinancialTweets_{hour}$	An indicator equal to 1 if at least 1 of the company's tweets discusses financial information on a given hour, 0 otherwise.
$Format\|Financial_{hour}$	An indicator equal to 1 if a financial tweet by a company on a given hour contains media or a hyperlink.
Independent variables	
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.
Form_10-K, 10-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.
Form_8-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.
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.
Neg_News	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).
Pos_News	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).
$Neg\_CAR_{(-1,+1)}$	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%).
$Period_{(-3h,+3h)}$	An indicator equal to 1 for the period 3 hours before an event up to 3 hours after.
Feedback_lag	An indicator equal to 1 when a financial tweet received a like, retweet, or reply on the previous announcement.
Control Variables	
Verified	An indicator equal to 1 if the company's Twitter account has been verified, 0 otherwise.
Followers	The number of Twitter followers the company's Twitter account had.

Friends	The number of accounts that the company's Twitter account is following.
Recent_Tweets	The number of tweets in the 5 trading days leading up to the current day.
Total_Tweets	Total number of tweets the company posted through the end of the sample period, December 31, 2016.
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 total 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).

Appendix B. Twitter Topics

Each of the topics below is comprised of one or more similar topics from the Twitter-LDA algorithm. 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.

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

Appendix C. News Event Categorization

We identified 15 news event types from the RavenPack Entity Mapping File. 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.

We further decompose $News\ Financial$ into Negative and Positive news based on the sign of the news. We identify the sign of the news from the "property" field in RavenPack using the following classification:

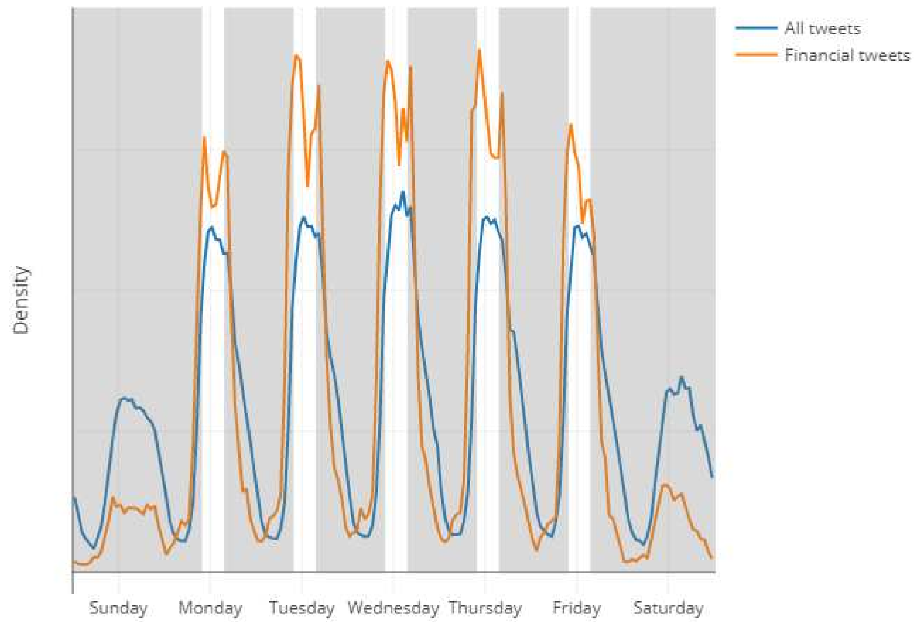
> *Negative*: Revised down, Below expectations, Delayed, Negative; Down;
> *Positive:* Revised up, Above expectations, Meets expectations, Positive, Up.

Event	**Event categories**
News_Financial	Comparisons or announcements of earnings, EBIT, EBITA, EBITDA, revenue or gross profit; EPS; earnings revisions
News_Merger	Bids, bid rejections, blocks, completions, delays, failures, opposition, regulatory approval, regulatory scrutiny, or termination fees tied to mergers, acquisitions, or unit acquisitions; 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

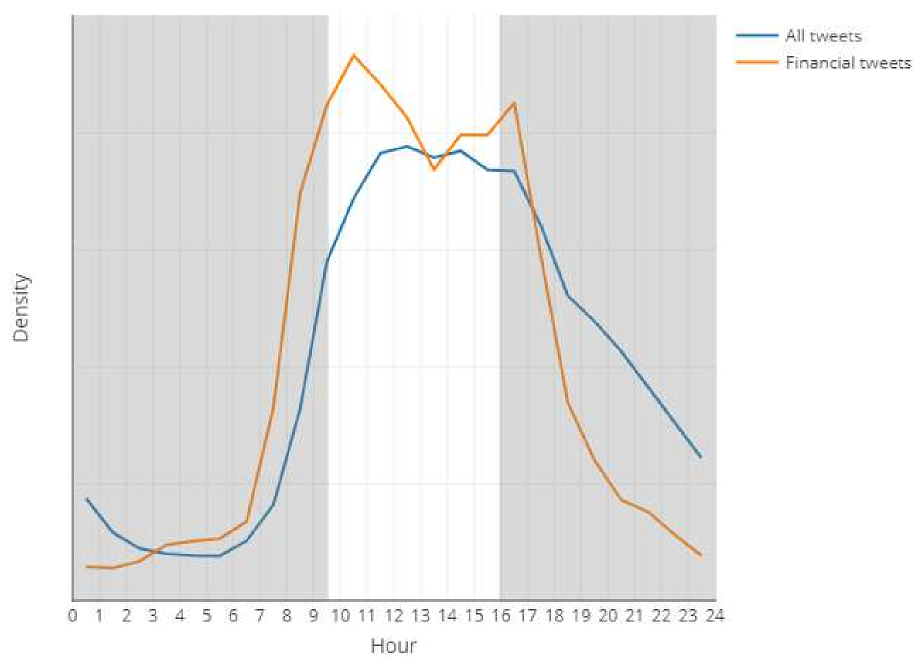
Figures

Figure 1: Distribution of tweets by time

Panel A: Tweets by hour within week



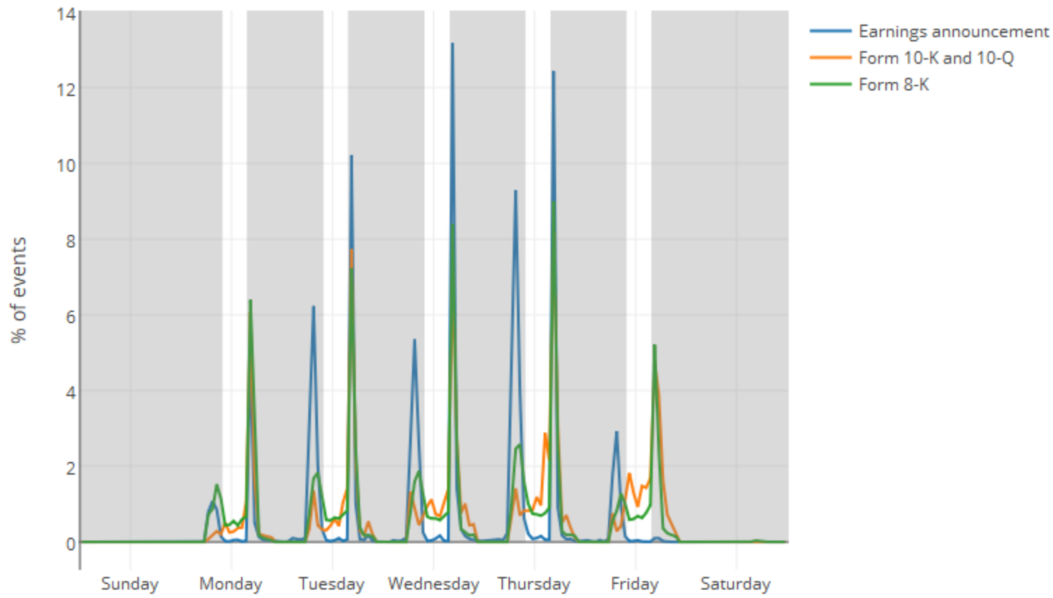
Panel B: Tweets by hour within day



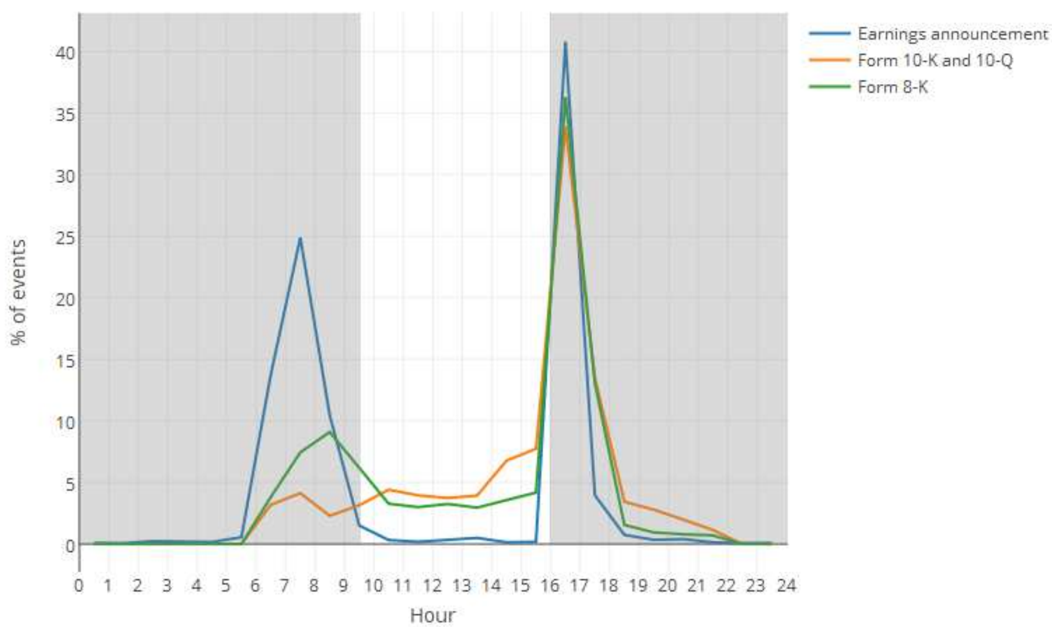
This figure shows the distribution of companies' tweets and financial tweets by hour of the week and hour of the day. The background is white during hours when the NYSE is open and gray when it is closed.

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
$Format$	0.594	1.00	0.491	0	1.00
$Format\|Financial$	0.0283	0	0.166	0	0
$Earnings\_Ann$	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
$Neg\_News_{(-1,+1)}$	0.0171	0	0.130	0	0
$Pos\_News_{(-1,+1)}$	0.0440	0	0.205	0	0
$CAR_{(-1,1)}$	-0.0001	0.0005	0.0351	-0.0303	0.0300
$Verified$	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 1,229,734 observations, except for all CAR measures at 1,186,800 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: Twitter adoption determinants

	(1) Financial *logit*	Z
$Size$	0.425***	[18.6]
ROA	0.151	[0.560]
MB	0.255***	[8.57]
$Debt$	0.171	[1.21]
$Volatility$	3.43	[1.39]
$Cons$	−4.73***	[−15.9]
$Year\ FE$	Included	
2013	0.228***	[2.85]
2014	0.481***	[5.86]
2015	0.696***	[8.19]
2016	0.846***	[8.89]
$Industry\ FE$	Included	
$Materials$ (15)	0.297**	[2.02]
$Industrials$ (20)	1.20***	[9.05]
$Consumer\ Discretionary$ (25)	1.91***	[13.8]
$Consumer\ Staples$ (30)	0.940***	[5.43]
$Health\ Care$ (35)	1.12***	[8.08]
$Financials$ (40)	0.682***	[5.18]
$Information\ Technology$ (45)	2.46***	[17.8]
$Communication\ Services$ (50)	2.49***	[7.19]
$Utilities$ (55)	1.29***	[6.56]
$Real\ Estate$ (60)	0.496***	[3.28]
$Month\ FE$	Included	
N	7210	
Pseudo R2	0.136	

The regression is run on the full firm-year sample. The dependent variable for the regression is $Joined\_Twitter$, an indicator for if a firm had a Twitter account with at least 1 tweet posted by December 31st of the given year. Variable definitions for all variables are included in Appendix A. The significance levels for all coefficient are denoted as follows: *** denotes $p < 0.01$, ** denotes $p < 0.05$, and * denotes $p < 0.10$. Z statistics are presented in square brackets.

Table 3: Tweeting activity

	(1) Financial *logit*	*Z*	(2) Financial *logit*	*Z*
$Earnings\_Ann$	0.926***	[40.6]	0.717***	[31.5]
$Form\_10\text{-}K, 10\text{-}Q$	0.149***	[6.73]	0.103***	[4.62]
$Form\_8\text{-}K$	0.0093	[0.560]		
$News\_Merger$			0.0970***	[5.22]
$News\_Financial$			0.150***	[8.13]
$News\_MgmtForecast$			0.350***	[13.8]
$News\_Exec$			0.127***	[6.85]
$News\_Analyst$			0.0162	[0.420]
$News\_ExecTrade$			−0.0155	[−1.15]
$Verified$	0.0496***	[3.31]	0.0686***	[4.57]
$\log(Followers)$	0.160***	[34.7]	0.154***	[33.1]
$\log(Friends)$	−0.101***	[−26.2]	−0.0960***	[−24.8]
$Recent\_Tweets$	2.24***	[81.8]	2.24***	[81.9]
$\log(Total\_Tweets)$	0.253***	[35.5]	0.247***	[34.8]
$Size$	−0.0433***	[−10.8]	−0.0574***	[−13.9]
ROA	0.779***	[9.76]	0.732***	[9.21]
MB	0.0499***	[13.3]	0.0482***	[12.8]
$Debt$	−0.385***	[−14.6]	−0.368***	[−14.1]
$Volatility$	3.90***	[8.15]	3.31***	[6.76]
$Cons$	−7.67***	[−115]	−7.48***	[−111]
$Year\ FE$	Included		Included	
$Month\ FE$	Included		Included	
$Industry\ FE$	Included		Included	
N	1229734		1229734	
Pseudo R2	0.162		0.163	

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. The significance levels for all coefficient are denoted as follows: *** denotes $p < 0.01$, ** denotes $p < 0.05$, and * denotes $p < 0.10$. Z statistics are presented in square brackets.

Table 4: Timing of financial tweets to major accounting events

Panel A, News classification based on RavenPack

	(1) Earnings Ann		(2) 10-K, 10-Q		(3) 8-K Filing	
	$logit$	Z	$logit$	Z	$logit$	Z
$Neg\_News_{(-1,+1)} \times Event$	1.34***	[33.2]	1.03***	[18.1]	1.03***	[27.5]
$Pos\_News_{(-1,+1)} \times Event$	1.19***	[52.8]	0.974***	[28.0]	1.00***	[46.6]
$Verified$	0.0506***	[3.38]	0.0506***	[3.39]	0.0527***	[3.52]
$\log(Followers)$	0.160***	[34.5]	0.160***	[34.5]	0.159***	[34.4]
$\log(Friends)$	−0.101***	[−26.1]	−0.0994***	[−25.8]	−0.102***	[−26.3]
$Recent\_Tweets$	2.24***	[81.8]	2.24***	[81.9]	2.24***	[81.9]
$\log(Total\_Tweets)$	0.253***	[35.5]	0.251***	[35.3]	0.249***	[35.0]
$Size$	−0.0451***	[−11.2]	−0.0439***	[−11.0]	−0.0482***	[−12.0]
ROA	0.782***	[9.80]	0.764***	[9.59]	0.755***	[9.46]
MB	0.0493***	[13.1]	0.0491***	[13.1]	0.0499***	[13.3]
$Debt$	−0.381***	[−14.5]	−0.379***	[−14.5]	−0.384***	[−14.6]
$Volatility$	3.77***	[7.87]	3.36***	[6.87]	3.29***	[6.72]
$Cons$	−7.63***	[−115]	−7.56***	[−114]	−7.55***	[−113]
$Year\ FE$	Included		Included		Included	
$Month\ FE$	Included		Included		Included	
$Industry\ FE$	Included		Included		Included	
N	1229734		1229734		1229734	
Pseudo R2	0.163		0.157		0.161	

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

	(1) Earnings Ann logit	Z	(2) 10-K, 10-Q logit	Z	(3) 8-K Filing logit	Z
$Neg\_CAR_{(-1,+1)} \times Event$	1.03***	[27.8]	0.742***	[13.1]	0.730***	[22.4]
$Pos\_CAR_{(-1,+1)} \times Event$	0.888***	[22.1]	0.707***	[11.1]	0.598***	[16.7]
$Verified$	0.0713***	[4.70]	0.0724***	[4.78]	0.0704***	[4.64]
$\log(Followers)$	0.160***	[34.2]	0.160***	[34.2]	0.161***	[34.3]
$\log(Friends)$	−0.0971***	[−24.6]	−0.0965***	[−24.5]	−0.0970***	[−24.6]
$Recent\_Tweets$	2.25***	[80.4]	2.26***	[80.5]	2.26***	[80.5]
$\log(Total\_Tweets)$	0.261***	[35.9]	0.260***	[35.8]	0.259***	[35.7]
$Size$	−0.0516***	[−12.7]	−0.0516***	[−12.7]	−0.0528***	[−13.0]
ROA	0.725***	[9.00]	0.722***	[8.97]	0.719***	[8.91]
MB	0.0494***	[12.9]	0.0494***	[12.9]	0.0500***	[13.1]
$Debt$	−0.389***	[−14.8]	−0.389***	[−14.8]	−0.391***	[−14.8]
$Volatility$	3.44***	[6.99]	3.24***	[6.52]	3.02***	[6.06]
$Cons$	−7.60***	[−113]	−7.56***	[−112]	−7.57***	[−112]
$Year\ FE$	Included		Included		Included	
$Month\ FE$	Included		Included		Included	
$Industry\ FE$	Included		Included		Included	
N	1186800		1186800		1186800	
Pseudo R2	0.163		0.161		0.162	

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, 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. The significance levels for all coefficient are denoted as follows: *** denotes $p < 0.01$, ** denotes $p < 0.05$, and * denotes $p < 0.10$. Z statistics are presented in square brackets.

Table 5: Tweet format

	(1) Financial $logit$	Z	(2) Financial $logit$	Z
$Earnings\_Ann$	0.947***	[38.4]	0.724***	[29.4]
$Form\_10\text{-}K, 10\text{-}Q$	0.162***	[6.74]	0.115***	[4.74]
$Form\_8\text{-}K$	−0.0099	[−0.540]		
$News\_Merger$			0.112***	[5.57]
$News\_Financial$			0.134***	[6.64]
$News\_MgmtForecast$			0.375***	[13.7]
$News\_Exec$			0.129***	[6.40]
$News\_Analyst$			0.0045	[0.110]
$News\_ExecTrade$			−0.0089	[−0.610]
$Verified$	0.0202	[1.24]	0.0390**	[2.40]
$\log(Followers)$	0.182***	[35.9]	0.175***	[34.5]
$\log(Friends)$	−0.118***	[−27.6]	−0.113***	[−26.4]
$Recent\_Tweets$	0.927***	[29.3]	0.933***	[29.5]
$\log(Total\_Tweets)$	0.147***	[18.3]	0.141***	[17.6]
$Size$	−0.0616***	[−14.1]	−0.0764***	[−16.9]
ROA	0.424***	[5.05]	0.381***	[4.55]
MB	0.0409***	[9.94]	0.0390***	[9.47]
$Debt$	−0.383***	[−13.1]	−0.366***	[−12.5]
$Volatility$	3.20***	[5.98]	2.58***	[4.76]
$Cons$	−5.59***	[−75.4]	−5.40***	[−71.9]
$Year\ FE$	Included		Included	
$Month\ FE$	Included		Included	
$Industry\ FE$	Included		Included	
N	805383		805383	
Pseudo R2	0.110		0.112	

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. The significance levels for all coefficient are denoted as follows: *** denotes $p < 0.01$, ** denotes $p < 0.05$, and * denotes $p < 0.10$. Z statistics are presented in square brackets.

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

Panel A, News classification based on RavenPack

	(1) Earnings Ann		(2) 10-K, 10-Q		(3) 8-K Filing	
	logit	*Z*	*logit*	*Z*	*logit*	*Z*
$Neg\_News_{(-1,+1)} \times Event$	1.36***	[31.6]	1.02***	[16.6]	1.05***	[26.3]
$Pos\_News_{(-1,+1)} \times Event$	1.18***	[49.0]	1.01***	[27.1]	0.995***	[43.0]
$Verified$	0.0207	[1.28]	0.0209	[1.29]	0.0232	[1.43]
$\log(Followers)$	0.181***	[35.8]	0.181***	[35.9]	0.181***	[35.7]
$\log(Friends)$	−0.118***	[−27.6]	−0.116***	[−27.3]	−0.118***	[−27.7]
$Recent\_Tweets$	0.934***	[29.5]	0.919***	[29.1]	0.929***	[29.4]
$\log(Total\_Tweets)$	0.147***	[18.3]	0.145***	[18.1]	0.142***	[17.8]
$Size$	−0.0638***	[−14.6]	−0.0622***	[−14.2]	−0.0668***	[−15.3]
ROA	0.429***	[5.10]	0.410***	[4.88]	0.403***	[4.79]
MB	0.0404***	[9.81]	0.0404***	[9.83]	0.0409***	[9.94]
$Debt$	−0.380***	[−12.9]	−0.378***	[−13.0]	−0.384***	[−13.1]
$Volatility$	3.05***	[5.69]	2.59***	[4.79]	2.54***	[4.68]
$Cons$	−5.56***	[−75.0]	−5.47***	[−74.0]	−5.47***	[−73.9]
$Year\ FE$	Included		Included		Included	
$Month\ FE$	Included		Included		Included	
$Industry\ FE$	Included		Included		Included	
N	805383		805383		805383	
Pseudo R2	0.112		0.105		0.110	

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

	(1) Earnings Ann		(2) 10-K, 10-Q		(3) 8-K Filing	
	$logit$	Z	$logit$	Z	$logit$	Z
$Neg\_CAR_{(-1,+1)} \times Event$	1.08***	[27.4]	0.796***	[13.3]	0.740***	[21.1]
$Pos\_CAR_{(-1,+1)} \times Event$	0.908***	[21.1]	0.757***	[11.2]	0.617***	[16.0]
$Verified$	0.0421***	[2.56]	0.0433***	[2.64]	0.0414**	[2.52]
$\log(Followers)$	0.182***	[35.6]	0.182***	[35.6]	0.182***	[35.7]
$\log(Friends)$	−0.112***	[−25.7]	−0.111***	[−25.6]	−0.112***	[−25.7]
$Recent\_Tweets$	0.949***	[29.3]	0.950***	[29.3]	0.950***	[29.3]
$\log(Total\_Tweets)$	0.153***	[18.8]	0.152***	[18.7]	0.152***	[18.6]
$Size$	−0.0707***	[−16.0]	−0.0706***	[−16.0]	−0.0719***	[−16.3]
ROA	0.384***	[4.53]	0.380***	[4.48]	0.377***	[4.45]
MB	0.0392***	[9.38]	0.0393***	[9.41]	0.0398***	[9.53]
$Debt$	−0.382***	[−13.0]	−0.383***	[−13.1]	−0.385***	[−13.1]
$Volatility$	2.56***	[4.67]	2.31***	[4.21]	2.11***	[3.84]
$Cons$	−5.52***	[−73.6]	−5.48***	[−73.1]	−5.49***	[−73.2]
$Year\ FE$	Included		Included		Included	
$Month\ FE$	Included		Included		Included	
$Industry\ FE$	Included		Included		Included	
N	776808		776808		776808	
Pseudo R2	0.111		0.108		0.109	

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, 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. The significance levels for all coefficient are denoted as follows: *** denotes $p < 0.01$, ** denotes $p < 0.05$, and * denotes $p < 0.10$. Z statistics are presented in square brackets.

Table 7: Descriptive statistics for intraday and feedback tests

Panel A: Hourly rates of financial tweeting during the 24 hours around events

	Earnings Ann	10-K, 10-Q	8-K Filing
Within $(-3, +3)$ hours of the event	$1.6\%^{***}$	$0.39\%^{***}$	$0.63\%^{***}$
Outside $(-3, +3)$ hours from the event	0.28%	0.17%	0.15%
Difference (within − outside)	1.3%	0.22%	0.48%
Difference t-statistic	[48.8]	[12.8]	[47.7]

Panel B: Hourly rates of financial tweet format during the 24 hours around events

	Earnings Ann	10-K, 10-Q	8-K Filing
Within $(-3, +3)$ hours of the event	$1.9\%^{***}$	$0.47\%^{***}$	$0.76\%^{***}$
Outside $(-3, +3)$ hours from the event	0.31%	0.21%	0.17%
Difference (within − outside)	1.6%	0.26%	0.59%
Difference t-statistic	[47.2]	[11.4]	[44.3]

Panel C: Feedback rates by event

	Earnings Ann	10-K, 10-Q	8-K Filing
$Feedback\_lag$	1.6%	0.83%	0.91%
N (event window days)	58397	58365	175885

Panel D: Financial tweet dissemination after feedback

	Earnings Ann	10-K, 10-Q	8-K Filing
$FinancialTweets$ after feedback	$41.4\%^{***}$	$24.1\%^{***}$	$14.8\%^{***}$
$FinancialTweets$ without feedback	7.00%	4.63%	4.62%
Difference (after − without)	34.4%	19.4%	10.2%
Difference t-statistic	[39.5]	[20.0]	[19.2]

Panel E: Financial tweet format after feedback

	Earnings Ann	10-K, 10-Q	8-K Filing
$Format \vert Financial$ after feedback	$43.8\%^{***}$	$27.2\%^{***}$	$16.9\%^{***}$
$Format \vert Financial$ without feedback	8.88%	5.93%	5.74%
Difference (after − without)	34.9%	21.2%	11.1%
Difference t-statistic	[32.1]	[16.7]	[16.2]

Panels A and B examines univariate differences in hourly financial tweeting behavior. The $(-3, +3)$ hour window corresponds to the $Period_{(-3h,+3h)}$ variable used in the hourly regression tests in Table 8. The sample for each difference is the 12 hours before and 12 hours after each event. Panel A examines the presence of financial tweets, while Panel B examines the format of financial tweets. Panel C presents univariate statistics for $Feedback\_lag$ by event. Panels D and E examine univariate differences in the presence and format of financial tweets conditional on $Feedback\_lag$. The sample only includes events where the firm has previously released a financial tweet during the same type of event. Variable definitions for all variables are included in Appendix A. Methodology for Twitter topics is discussed in Appendix B. The significance levels for all t-tests are denoted as follows: *** denotes $p < 0.01$, ** denotes $p < 0.05$, and * denotes $p < 0.10$. T-statistics are presented in square brackets.

Table 8: Hourly tweeting around events

Panel A, Financial Tweets

	(1) Earnings Ann		(2) 10-K, 10-Q		(3) 8-K Filing	
	logit	Z	*logit*	Z	*logit*	Z
$Period_{(-3h,+3h)}$	1.31***	[27.5]	0.560***	[7.65]	1.05***	[29.3]
$Verified$	0.232***	[4.18]	0.324***	[3.51]	0.220***	[4.52]
$\log(Followers)$	−0.0262	[−1.44]	−0.0528*	[−1.73]	0.0303**	[1.96]
$\log(Friends)$	0.0300**	[2.03]	−0.0025	[−0.100]	−0.0200	[−1.59]
$Recent\_Tweets$	0.937***	[11.9]	1.01***	[7.24]	1.12***	[15.7]
$\log(Total\_Tweets)$	0.0262	[1.02]	0.138***	[3.16]	0.0646***	[2.90]
$Size$	0.367***	[22.4]	0.208***	[7.64]	0.180***	[13.5]
ROA	0.0876	[0.280]	−0.0495	[−0.0800]	0.882***	[2.91]
MB	0.146***	[10.2]	0.0494*	[1.69]	0.0916***	[6.87]
$Debt$	−0.229**	[−2.18]	−0.742***	[−4.00]	−0.536***	[−5.58]
$Volatility$	−6.94**	[−2.44]	−27.1***	[−6.20]	−8.54***	[−4.14]
$Cons$	−12.8***	[−20.6]	−10.6***	[−16.2]	−11.8***	[−26.2]
$Year\ FE$	Included		Included		Included	
$Month\ FE$	Included		Included		Included	
$Industry\ FE$	Included		Included		Included	
$Hour\ at\ NYSE\ FE$	Included		Included		Included	
N	462048		427320		1377768	
Pseudo R2	0.220		0.144		0.152	

Panel B, Financial tweet format

	(1) Earnings Ann *logit*	*Z*	(2) 10-K, 10-Q *logit*	*Z*	(3) 8-K Filing *logit*	*Z*
$Period_{(-3h,+3h)}$	1.38***	[26.1]	0.545***	[6.69]	1.05***	[26.8]
$Verified$	0.140**	[2.32]	0.282***	[2.76]	0.166***	[3.12]
$\log(Followers)$	0.0035	[0.170]	−0.0251	[−0.710]	0.0670***	[3.87]
$\log(Friends)$	0.0361**	[2.22]	−0.0268	[−0.980]	−0.0253*	[−1.82]
$Recent\_Tweets$	−0.0311	[−0.350]	−0.296*	[−1.82]	−0.0387	[−0.480]
$\log(Total\_Tweets)$	−0.0633**	[−2.11]	0.0984*	[1.90]	−0.0483*	[−1.86]
$Size$	0.329***	[18.0]	0.152***	[4.92]	0.152***	[10.2]
ROA	−0.249	[−0.820]	−0.416	[−0.590]	0.326	[1.01]
MB	0.135***	[8.98]	0.0158	[0.450]	0.0901***	[6.25]
$Debt$	−0.0924	[−0.810]	−0.510**	[−2.51]	−0.424***	[−4.02]
$Volatility$	−6.18*	[−1.95]	−37.1***	[−7.14]	−11.7***	[−4.94]
$Cons$	−11.2***	[−17.7]	−9.73***	[−8.80]	−9.79***	[−21.3]
$Year\ FE$	Included		Included		Included	
$Month\ FE$	Included		Included		Included	
$Industry\ FE$	Included		Included		Included	
$Hour\ at\ NYSE\ FE$	Included		Included		Included	
N	328296		287160		955200	
Pseudo R2	0.211		0.133		0.137	

Panel A examines the presence of financial tweets, while Panel B examines the format of financial tweets. In Panel A, regressions are run on the hour-basis sample from 24 hour windows around events contained in the full day-basis sample; in Panel B, regressions are run on the hour-basis sample from 24 hour windows around events contained in the day-basis sample restricted to firm-days with at least 1 tweet. The dependent variable for all regressions in Panel A is $FinancialTweets_{hour}$, an indicator for if a company posted a financial tweet in a given hour; the dependent variable for all regressions in Panel B is $Format|Financial_{hour}$, an indicator for if a company posted a financial tweet containing a link or media in a given hour. Variable definitions for all variables are included in Appendix A. The significance levels for all coefficient are denoted as follows: *** denotes $p < 0.01$, ** denotes $p < 0.05$, and * denotes $p < 0.10$. Z statistics are presented in square brackets.

Table 9: Feedback effects on tweeting

Panel A, Financial tweets

	(1) Earnings Ann		(2) 10-K, 10-Q		(3) 8-K Filing	
	$logit$	Z	$logit$	Z	$logit$	Z
$Feedback\_lag(Event)$	2.31***	[30.9]	1.84***	[15.8]	1.24***	[16.6]
$Verified$	0.0474	[0.990]	0.0727	[1.26]	0.0590*	[1.73]
$\log(Followers)$	0.0449***	[2.94]	0.0696***	[3.75]	0.110***	[10.3]
$\log(Friends)$	−0.0291**	[−2.35]	−0.0260*	[−1.71]	−0.0625***	[−7.17]
$Recent\_Tweets$	1.21***	[18.2]	1.59***	[17.7]	1.60***	[30.6]
$\log(Total\_Tweets)$	0.122***	[5.49]	0.174***	[6.34]	0.129***	[8.16]
$Size$	0.198***	[14.5]	0.0309*	[1.87]	0.0290***	[3.22]
ROA	0.0362	[0.160]	0.261	[0.830]	0.0634	[0.350]
MB	0.107***	[9.14]	0.0527***	[3.41]	0.0677***	[7.28]
$Debt$	−0.227***	[−2.65]	−0.467***	[−4.40]	−0.368***	[−5.77]
$Volatility$	−3.44*	[−1.73]	−11.6***	[−5.46]	−0.585	[−0.540]
$Cons$	−6.07***	[−31.5]	−5.15***	[−20.0]	−5.81***	[−43.8]
$Year\ FE$	Included		Included		Included	
$Month\ FE$	Included		Included		Included	
$Industry\ FE$	Included		Included		Included	
N	58397		58365		175885	
Pseudo R2	0.110		0.105		0.0996	

Panel B, Financial tweet format

	(1) Earnings Ann		(2) 10-K, 10-Q		(3) 8-K Filing	
	logit	*Z*	*logit*	*Z*	*logit*	*Z*
$Feedback\_lag(Event)$	1.92***	[23.6]	1.61***	[12.7]	1.06***	[12.9]
$Verified$	−0.0007	[−0.0100]	0.0413	[0.660]	0.0446	[1.21]
log($Followers$)	0.0740***	[4.43]	0.107***	[5.26]	0.138***	[11.8]
log($Friends$)	−0.0451***	[−3.38]	−0.0520***	[−3.17]	−0.0823***	[−8.61]
$Recent\_Tweets$	−0.0890	[−1.18]	0.143	[1.39]	0.295***	[4.93]
log($Total\_Tweets$)	0.0031	[0.120]	0.0917***	[2.98]	−0.0063	[−0.350]
$Size$	0.180***	[12.2]	−0.0021	[−0.120]	0.0089	[0.900]
ROA	−0.224	[−0.890]	−0.148	[−0.430]	−0.343*	[−1.76]
MB	0.101***	[7.82]	0.0446***	[2.63]	0.0665***	[6.63]
$Debt$	−0.136	[−1.46]	−0.436***	[−3.73]	−0.346***	[−4.93]
$Volatility$	−1.42	[−0.670]	−13.5***	[−5.79]	−1.48	[−1.23]
$Cons$	−4.10***	[−19.4]	−2.90***	[−10.4]	−3.57***	[−24.1]
$Year\ FE$	Included		Included		Included	
$Month\ FE$	Included		Included		Included	
$Industry\ FE$	Included		Included		Included	
N	40037		38847		119014	
Pseudo R2	0.0769		0.0647		0.0610	

Panel A examines the presence of financial tweets, while Panel B examines the format of financial tweets. In Panel A, regressions are run on the full day-basis sample; in Panel B, regressions are run on the day-basis sample restricted to firm-days with at least 1 tweet. The dependent variable for all regressions in Panel A is $FinancialTweets$, an indicator for if a company posted a financial tweet on a given trading day; the dependent variable for all regressions in Panel B 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. The significance levels for all coefficient are denoted as follows: *** denotes $p < 0.01$, ** denotes $p < 0.05$, and * denotes $p < 0.10$. Z statistics are presented in square brackets.

Online appendix for "Discretionary Dissemination on Twitter"

Online 1 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).
$FinancialTweets_{Dict}$	An indicator equal to 1 if at least 1 of the company's tweets discusses financial information on a given day following the dictionary approach of Jung et al. (2018), 0 otherwise (Twitter API).

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).
$News\_[Event]$	News indicator regarding an event $[Event]$, based on hand classification of Ravenpack's news event taxonomy. Specific events are detailed in Appendix C of the main paper.
$Neg\_News_{(-1,+1)}$	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).
$Pos\_News_{(-1,+1)}$	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).
$Neg\_CAR_{(-1,+1)}$	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: Splits

Variable	Definition
Lit	Litigation score following Jung et al. (2018), Kim and Skinner (2012), and Johnson, Kasznick and Nelson (2000) (Stanford Class Action Clearninghouse, Compustat, CRSP).
$Retail$	The percent of shares owned by retail investors, defined as 1 minus the percent of shares owned by institutional investors as of the most recent 13F filings to the observation (WRDS SEC Analytics Suite 13F Holdings).
$Followers$	The number of Twitter followers the company's Twitter account has (Twitter API).

Panel D: 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).

Tables

Table A1: Correlation matrices

Panel A: Independent and dependent variable correlations

	$Tweets$	$FinancialTweets$	$Format$	$Format \mid Financial$
$Earnings\_Ann$	**0.0144**	**0.0513**	**0.0154**	**0.0496**
$Form\_10\text{-}K, 10\text{-}Q$	**0.0050**	**0.0175**	**0.0057**	**0.0168**
$Form\_8\text{-}K$	**0.0187**	**0.0301**	**0.0171**	**0.0278**
$News\_Merger$	**0.0395**	**0.0292**	**0.0429**	**0.0273**
$News\_Financial$	**0.0371**	**0.0467**	**0.0382**	**0.0430**
$News\_MgmtForecast$	**0.0246**	**0.0381**	**0.0271**	**0.0365**
$News\_Exec$	**0.0584**	**0.0359**	**0.0592**	**0.0324**
$News\_Analyst$	**0.0204**	**0.0229**	**0.0207**	**0.0200**
$News\_ExecTrade$	**0.0218**	**0.0068**	**0.0238**	**0.0065**
$Neg\_News_{(-1,+1)}$	**0.0170**	**0.0218**	**0.0168**	**0.0209**
$Pos\_News_{(-1,+1)}$	**0.0294**	**0.0449**	**0.0297**	**0.0410**
$CAR_{(-1,1)}$	−0.0008	−0.0014	−0.0007	−0.0012

Panel B: Control and dependent variable correlations

	$Tweets$	$FinancialTweets$	$Format$	$Format \mid Financial$
$Verified$	**0.299**	**0.0865**	**0.272**	**0.0715**
$Followers$	**0.0728**	**0.0728**	**0.0743**	**0.0683**
$Friends$	**0.0762**	**0.0127**	**0.0771**	0.0011
$Recent\_Tweets$	**0.710**	**0.123**	**0.655**	**0.112**
$Total\_Tweets$	**0.151**	**0.0673**	**0.156**	**0.0310**
$Size$	**0.107**	**0.0718**	**0.0899**	**0.0639**
ROA	**0.0820**	**0.0310**	**0.0808**	**0.0238**
MB	**0.0766**	**0.0342**	**0.0876**	**0.0277**
$Debt$	**0.0552**	**0.0201**	**0.0334**	**0.0179**
$Volatility$	**−0.0485**	**−0.0176**	**−0.0363**	**−0.0162**

Panel C: Control variable correlations

	Volatility	*Debt*	*MB*	*ROA*	*Size*	*Total_Tweets*	*Recent_Tweets*	*Friends*	*Followers*	*Verified*
Verified	**−0.0593**	**0.128**	**0.0589**	**0.0919**	**0.333**	**0.264**	**0.367**	**0.137**	**0.198**	1.00
Followers	**−0.0088**	**−0.0140**	**0.0903**	**0.0391**	**0.0780**	**0.297**	**0.0892**	**0.175**	1.00	
Friends	**−0.0096**	**−0.0022**	**0.0422**	**0.0287**	**0.0265**	**0.277**	**0.0935**	1.00		
Recent_Tweets	**−0.0573**	**0.0678**	**0.0941**	**0.100**	**0.132**	**0.185**	1.00			
Total_Tweets	**−0.0136**	**0.0763**	**0.0707**	**0.0681**	**0.0931**	1.00				
Size	**−0.236**	**0.439**	**−0.337**	**−0.0228**	1.00					
ROA	**−0.231**	**−0.148**	**0.420**	1.00						
MB	**−0.0251**	**−0.281**	1.00							
Debt	**−0.0575**	1.00								
Volatility	1.00									

Variable definitions for all variables are included in Appendix A of the main paper. Bold numbers are significantly different from zero at $p < 0.05$

Table A2: Additional summary statistics

Panel A: Descriptive statistics for dependent and splitting variables

	Mean	Median	SD	p10	p90
$FinancialTweets$	0.0338	0	0.181	0	0
$FinancialTweets_{Dict}$	0.104	0	0.305	0	1.00
$Retail$	0.115	0.0583	0.147	0	0.318
$Litigation$	0.0168	0.0118	0.0246	0.0070	0.0291
$Followers$	98695	4339	736019	424	104470

Panel B: Agreement between financial tweet measures

Percentage	$FinancialTweet_{Dict} = 0$	$FinancialTweet_{Dict} = 1$
$FinancialTweet = 0$	87.5%	9.15%
$FinancialTweet = 1$	2.13%	1.25%

Days	$FinancialTweet_{Dict} = 0$	$FinancialTweet_{Dict} = 1$
$FinancialTweet = 0$	1,075,965	112,569
$FinancialTweet = 1$	26,205	15,366

Panel C: Percent of tweets around financial events by financial tweet measure

	Earnings Announcements	10-K and 10-Q Filings	8-K Filings
Window: $(-1, +1)$			
$FinancialTweet$	10.6%***	6.73%***	19.9%***
$FinancialTweet_{Dict}$	7.83%	5.78%	18.2%
Window: day of event			
$FinancialTweet$	5.45%***	2.71%***	9.29%***
$FinancialTweet_{Dict}$	3.56%	2.17%	7.59%

Variable definitions for all variables are included in Appendix Online 1. Methodology for news events is discussed in Appendix C of the main paper. The significance levels for all Z-test of difference in proportions (Panel C) are denoted as follows: *** denotes $p < 0.01$, ** denotes $p < 0.05$, and * denotes $p < 0.10$.

Table A3: Tweeting activity, Dictionary approach

	(1) $FinancialTweets_{Dict}$ logit	Z	(2) $FinancialTweets_{Dict}$ logit	Z
$Earnings\_Ann$	0.767***	[45.5]	0.610***	[35.6]
$Form\_10\text{-}K, 10\text{-}Q$	0.0788***	[5.02]	0.0404**	[2.56]
$Form\_8\text{-}K$	0.0406***	[3.78]		
$News\_Merger$			0.0545***	[4.55]
$News\_Financial$			0.255***	[21.3]
$News\_MgmtForecast$			0.117***	[6.26]
$News\_Exec$			0.0551***	[4.57]
$News\_Analyst$			−0.0887***	[−3.37]
$News\_ExecTrade$			−0.0431***	[−4.94]
$Verified$	2.47***	[233]	2.48***	[234]
$\log(Followers)$	−0.0405***	[−14.2]	−0.0435***	[−15.2]
$\log(Friends)$	−0.0898***	[−35.5]	−0.0893***	[−35.3]
$Recent\_Tweets$	1.91***	[105]	1.91***	[106]
$\log(Total\_Tweets)$	0.186***	[41.0]	0.185***	[40.8]
$Size$	0.0971***	[37.5]	0.0881***	[32.8]
ROA	−1.05***	[−24.5]	−1.06***	[−24.8]
MB	0.0480***	[19.0]	0.0469***	[18.5]
$Debt$	−0.847***	[−49.5]	−0.842***	[−49.2]
$Volatility$	−0.649*	[−1.90]	−1.19***	[−3.45]
$Cons$	−6.24***	[−144]	−6.14***	[−140]
$Year\ FE$	Included		Included	
$Month\ FE$	Included		Included	
$Industry\ FE$	Included		Included	
N	1229734		1229734	
Pseudo R2	0.289		0.290	

All regressions are run on the full day-basis sample. The dependent variable for all regressions is $FinancialTweets_{Dict}$, an indicator for if a company posted a financial tweet (classified by a dictionary approach) on a given trading day. Variable definitions for all variables are included in Appendix A and Appendix Online 1. Methodology for news events is discussed in Appendix C. The significance levels for all coefficient are denoted as follows: *** denotes $p < 0.01$, ** denotes $p < 0.05$, and * denotes $p < 0.10$. Z statistics are presented in square brackets.

Table A4: Splits on timing of financial tweets to earnings announcements

Panel A, News classification based on RavenPack

	(1) High Litigation		(2) High Retail		(3) High Followers	
	$logit$	Z	$logit$	Z	$logit$	Z
$Neg\_News_{(-1,+1)} \times Earnings\_Ann$	1.36***	[21.0]	1.29***	[16.8]	1.81***	[19.7]
$Pos\_News_{(-1,+1)} \times Earnings\_Ann$	1.23***	[37.5]	1.14***	[29.9]	1.42***	[30.4]
$Neg\_News \times Earnings\_Ann \times High\_Split$	−0.0530	[−0.640]	0.0887	[0.910]	−0.556***	[−5.46]
$Pos\_News \times Earnings\_Ann \times High\_Split$	−0.0675	[−1.54]	0.107**	[2.11]	−0.292***	[−5.55]
$Verified$	0.0547***	[3.64]	0.0084	[0.480]	0.0492***	[3.28]
$\log(Followers)$	0.161***	[34.6]	0.171***	[32.2]	0.163***	[35.0]
$\log(Friends)$	−0.100***	[−25.9]	−0.103***	[−22.4]	−0.100***	[−25.9]
$Recent\_Tweets$	2.24***	[81.5]	2.22***	[66.3]	2.25***	[81.9]
$\log(Total\_Tweets)$	0.249***	[34.8]	0.277***	[33.7]	0.253***	[35.5]
$Size$	−0.0440***	[−10.9]	−0.0633***	[−13.3]	−0.0448***	[−11.2]
ROA	0.730***	[9.11]	0.567***	[6.32]	0.788***	[9.89]
MB	0.0566***	[14.7]	0.0490***	[11.5]	0.0492***	[13.1]
$Debt$	−0.372***	[−14.2]	−0.497***	[−16.3]	−0.380***	[−14.5]
$Volatility$	3.96***	[8.32]	4.17***	[7.96]	3.77***	[7.88]
$Cons$	−7.75***	[−112]	−7.72***	[−97.8]	−7.74***	[−113]
$Year\ FE$	Included		Included		Included	
$Month\ FE$	Included		Included		Included	
$Industry\ FE$	Included		Included		Included	
News impact difference	Difference	$\chi^2 stat$	Difference	$\chi^2 stat$	Difference	$\chi^2 stat$
$Neg\_News \neq Pos\_News \mid High\_Split$	0.151**	(6.45)	0.136**	(3.89)	0.120**	(5.60)
N	1218591		883004		1229734	
Pseudo R2	0.164		0.166		0.163	

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

	(1) High Litigation *logit*	Z	(2) High Retail *logit*	Z	(3) High Followers *logit*	Z
$Neg\_CAR_{(-1,+1)} \times Earnings\_Ann$	1.06***	[18.6]	1.04***	[16.5]	1.32***	[16.2]
$Pos\_CAR_{(-1,+1)} \times Earnings\_Ann$	0.934***	[16.0]	0.785***	[11.1]	1.12***	[12.7]
$Neg\_CAR_{(-1,+1)} \times Earnings\_Ann \times High\_Split$	−0.0422	[−0.570]	−0.0335	[−0.390]	−0.349***	[−3.84]
$Pos\_CAR_{(-1,+1)} \times Earnings\_Ann \times High\_Split$	−0.101	[−1.26]	0.163*	[1.73]	−0.284***	[−2.87]
$Verified$	0.0725***	[4.77]	0.0211	[1.20]	0.0709***	[4.67]
$\log(Followers)$	0.161***	[34.4]	0.176***	[32.8]	0.162***	[34.5]
$\log(Friends)$	−0.0964***	[−24.5]	−0.0990***	[−21.2]	−0.0967***	[−24.6]
$Recent\_Tweets$	2.26***	[80.2]	2.24***	[65.3]	2.26***	[80.4]
$\log(Total\_Tweets)$	0.257***	[35.4]	0.283***	[34.0]	0.261***	[35.9]
$Size$	−0.0503***	[−12.4]	−0.0722***	[−15.0]	−0.0515***	[−12.7]
ROA	0.689***	[8.53]	0.513***	[5.67]	0.725***	[9.00]
MB	0.0545***	[14.1]	0.0475***	[11.0]	0.0494***	[12.9]
$Debt$	−0.387***	[−14.7]	−0.498***	[−16.4]	−0.389***	[−14.7]
$Volatility$	3.54***	[7.21]	3.71***	[6.84]	3.43***	[6.98]
$Cons$	−7.72***	[−111]	−7.70***	[−96.3]	−7.70***	[−111]
$Year\ FE$	Included		Included		Included	
$Month\ FE$	Included		Included		Included	
$Industry\ FE$	Included		Included		Included	
News impact difference	Difference	$\chi^2 stat$	Difference	$\chi^2 stat$	Difference	$\chi^2 stat$
$Neg\_News \neq Pos\_News \mid High\_Split$	0.183**	(6.25)	0.0582	(0.46)	0.134**	(4.87)
N	1178945		852283		1186800	
Pseudo R2	0.164		0.167		0.163	

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, 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. $High\_Split$ is equal to 1 if the variable used for splitting is above the median, and 0 otherwise. Variable definitions for all variables are included in Appendix A and Appendix Online 1. Methodology for Twitter topics is discussed in Appendix B. The significance levels for all coefficient are denoted as follows: *** denotes $p < 0.01$, ** denotes $p < 0.05$, and * denotes $p < 0.10$. Z statistics are presented in square brackets, and χ^2 statistics are presented in parentheses.

Table A5: Splits on timing of financial tweets to 10-K and 10-Q filings

Panel A, News classification based on RavenPack

	(1) High Litigation		(2) High Retail		(3) High Followers	
	$logit$	Z	$logit$	Z	$logit$	Z
$Neg\_News_{(-1,+1)} \times Form\_10\text{-}K,\ 10\text{-}Q$	1.03***	[11.8]	0.967***	[9.34]	1.50***	[12.6]
$Pos\_News_{(-1,+1)} \times Form\_10\text{-}K,\ 10\text{-}Q$	0.966***	[19.3]	0.981***	[17.6]	1.37***	[19.4]
$Neg\_News \times Form\_10\text{-}K,\ 10\text{-}Q \times High\_Split$	−0.0141	[−0.120]	0.137	[1.04]	−0.581***	[−4.30]
$Pos\_News \times Form\_10\text{-}K,\ 10\text{-}Q \times High\_Split$	0.0127	[0.180]	−0.0369	[−0.480]	−0.494***	[−6.14]
$Verified$	0.0543***	[3.63]	0.0087	[0.500]	0.0495***	[3.31]
$\log(Followers)$	0.161***	[34.7]	0.171***	[32.2]	0.161***	[34.9]
$\log(Friends)$	−0.0987***	[−25.5]	−0.101***	[−22.1]	−0.0990***	[−25.7]
$Recent\_Tweets$	2.24***	[81.6]	2.22***	[66.4]	2.24***	[82.0]
$\log(Total\_Tweets)$	0.247***	[34.6]	0.275***	[33.6]	0.251***	[35.4]
$Size$	−0.0430***	[−10.7]	−0.0620***	[−13.1]	−0.0436***	[−10.9]
ROA	0.717***	[8.96]	0.552***	[6.17]	0.769***	[9.66]
MB	0.0561***	[14.6]	0.0487***	[11.5]	0.0490***	[13.1]
$Debt$	−0.371***	[−14.2]	−0.495***	[−16.4]	−0.377***	[−14.4]
$Volatility$	3.54***	[7.28]	3.78***	[7.04]	3.36***	[6.87]
$Cons$	−7.68***	[−112]	−7.66***	[−97.1]	−7.67***	[−112]
$Year\ FE$	Included		Included		Included	
$Month\ FE$	Included		Included		Included	
$Industry\ FE$	Included		Included		Included	
News impact difference	Difference	$\chi^2 stat$	Difference	$\chi^2 stat$	Difference	$\chi^2 stat$
$Neg\_News \neq Pos\_News \mid High\_Split$	0.0345	(0.15)	0.159	(2.60)	0.0486	(0.42)
N	1218591		883004		1229734	
Pseudo R2	0.158		0.161		0.157	

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

	(1) High Litigation *logit*	*Z*	(2) High Retail *logit*	*Z*	(3) High Followers *logit*	*Z*
$Neg\_CAR_{(-1,+1)} \times Form\_10\text{-}K,\ 10\text{-}Q$	0.630***	[7.16]	0.956***	[10.9]	1.16***	[10.3]
$Pos\_CAR_{(-1,+1)} \times Form\_10\text{-}K,\ 10\text{-}Q$	0.762***	[8.49]	0.626***	[5.79]	0.862***	[6.14]
$Neg\_CAR_{(-1,+1)} \times Form\_10\text{-}K,\ 10\text{-}Q \times High\_Split$	0.192*	[1.67]	−0.410***	[−3.22]	−0.531***	[−4.08]
$Pos\_CAR_{(-1,+1)} \times Form\_10\text{-}K,\ 10\text{-}Q \times High\_Split$	−0.124	[−0.970]	0.168	[1.15]	−0.191	[−1.22]
$Verified$	0.0732***	[4.82]	0.0216	[1.22]	0.0721***	[4.75]
$\log(Followers)$	0.161***	[34.4]	0.176***	[32.8]	0.161***	[34.3]
$\log(Friends)$	−0.0958***	[−24.3]	−0.0984***	[−21.1]	−0.0963***	[−24.5]
$Recent\_Tweets$	2.26***	[80.4]	2.25***	[65.5]	2.26***	[80.6]
$\log(Total\_Tweets)$	0.256***	[35.3]	0.282***	[33.9]	0.260***	[35.8]
$Size$	−0.0505***	[−12.4]	−0.0720***	[−15.0]	−0.0515***	[−12.7]
ROA	0.690***	[8.54]	0.512***	[5.66]	0.724***	[8.99]
MB	0.0544***	[14.0]	0.0474***	[11.0]	0.0494***	[12.9]
$Debt$	−0.387***	[−14.7]	−0.500***	[−16.4]	−0.389***	[−14.8]
$Volatility$	3.34***	[6.73]	3.53***	[6.44]	3.24***	[6.52]
$Cons$	−7.68***	[−110]	−7.66***	[−96.0]	−7.66***	[−111]
$Year\ FE$	Included		Included		Included	
$Month\ FE$	Included		Included		Included	
$Industry\ FE$	Included		Included		Included	
News impact difference	Difference	$\chi^2 stat$	Difference	$\chi^2 stat$	Difference	$\chi^2 stat$
$Neg\_News \neq Pos\_News \mid High\_Split$	0.184	(2.48)	−0.248*	(3.35)	−0.0400	(0.17)
N	1178945		852283		1186800	
Pseudo R2	0.161		0.165		0.161	

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, 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. $High\_Split$ is equal to 1 if the variable used for splitting is above the median, and 0 otherwise. Variable definitions for all variables are included in Appendix A and Appendix Online 1. Methodology for Twitter topics is discussed in Appendix B. The significance levels for all coefficient are denoted as follows: *** denotes $p < 0.01$, ** denotes $p < 0.05$, and * denotes $p < 0.10$. Z statistics are presented in square brackets, and χ^2 statistics are presented in parentheses.

Table A6: Splits on timing of financial tweets to 8-K filings

Panel A, News classification based on RavenPack

	(1) High Litigation		(2) High Retail		(3) High Followers	
	$logit$	Z	$logit$	Z	$logit$	Z
$Neg\_News_{(-1,+1)} \times Form\_8\text{-}K$	1.07***	[17.6]	1.04***	[14.6]	1.53***	[17.7]
$Pos\_News_{(-1,+1)} \times Form\_8\text{-}K$	1.03***	[32.9]	1.00***	[27.7]	1.28***	[28.0]
$Neg\_News \times Form\_8\text{-}K \times High\_Split$	−0.0784	[−1.02]	−0.0036	[−0.0400]	−0.588***	[−6.18]
$Pos\_News \times Form\_8\text{-}K \times High\_Split$	−0.0554	[−1.33]	0.0134	[0.280]	−0.344***	[−6.74]
$Verified$	0.0568***	[3.78]	0.0117	[0.670]	0.0511***	[3.41]
$\log(Followers)$	0.161***	[34.5]	0.171***	[32.1]	0.163***	[35.0]
$\log(Friends)$	−0.101***	[−26.1]	−0.103***	[−22.4]	−0.101***	[−26.1]
$Recent\_Tweets$	2.25***	[81.6]	2.23***	[66.5]	2.25***	[82.1]
$\log(Total\_Tweets)$	0.245***	[34.3]	0.271***	[33.1]	0.249***	[35.0]
$Size$	−0.0471***	[−11.7]	−0.0664***	[−14.0]	−0.0477***	[−11.9]
ROA	0.705***	[8.80]	0.543***	[6.05]	0.761***	[9.54]
MB	0.0570***	[14.8]	0.0496***	[11.7]	0.0497***	[13.3]
$Debt$	−0.376***	[−14.3]	−0.500***	[−16.4]	−0.384***	[−14.6]
$Volatility$	3.49***	[7.16]	3.74***	[6.97]	3.29***	[6.74]
$Cons$	−7.66***	[−111]	−7.64***	[−96.8]	−7.67***	[−112]
$Year\ FE$	Included		Included		Included	
$Month\ FE$	Included		Included		Included	
$Industry\ FE$	Included		Included		Included	
News impact difference	Difference	$\chi^2 stat$	Difference	$\chi^2 stat$	Difference	$\chi^2 stat$
$Neg\_News \neq Pos\_News \mid High\_Split$	0.0134	(0.06)	0.0257	(0.16)	0.0002	(0.00)
N	1218591		883004		1229734	
Pseudo R2	0.162		0.165		0.162	

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

	(1) High Litigation *logit*	*Z*	(2) High Retail *logit*	*Z*	(3) High Followers *logit*	*Z*
$Neg\_CAR_{(-1,+1)} \times Form\_8\text{-}K$	0.757***	[14.9]	0.794***	[14.6]	0.938***	[12.8]
$Pos\_CAR_{(-1,+1)} \times Form\_8\text{-}K$	0.655***	[12.4]	0.584***	[9.42]	0.807***	[9.88]
$Neg\_CAR_{(-1,+1)} \times Form\_8\text{-}K \times High\_Split$	−0.0450	[−0.690]	−0.143*	[−1.90]	−0.254***	[−3.13]
$Pos\_CAR_{(-1,+1)} \times Form\_8\text{-}K \times High\_Split$	−0.116	[−1.62]	0.0378	[0.460]	−0.252***	[−2.79]
$Verified$	0.0718***	[4.72]	0.0199	[1.13]	0.0702***	[4.63]
$\log(Followers)$	0.162***	[34.5]	0.177***	[32.9]	0.162***	[34.5]
$\log(Friends)$	−0.0963***	[−24.4]	−0.0988***	[−21.2]	−0.0966***	[−24.5]
$Recent\_Tweets$	2.26***	[80.3]	2.24***	[65.4]	2.26***	[80.5]
$\log(Total\_Tweets)$	0.256***	[35.2]	0.281***	[33.8]	0.259***	[35.7]
$Size$	−0.0514***	[−12.6]	−0.0733***	[−15.3]	−0.0527***	[−13.0]
ROA	0.683***	[8.45]	0.506***	[5.58]	0.719***	[8.92]
MB	0.0550***	[14.2]	0.0480***	[11.2]	0.0500***	[13.1]
$Debt$	−0.390***	[−14.8]	−0.501***	[−16.4]	−0.391***	[−14.8]
$Volatility$	3.13***	[6.29]	3.32***	[6.02]	3.02***	[6.06]
$Cons$	−7.69***	[−110]	−7.67***	[−96.0]	−7.67***	[−111]
$Year\ FE$	Included		Included		Included	
$Month\ FE$	Included		Included		Included	
$Industry\ FE$	Included		Included		Included	
News impact difference	Difference	$\chi^2 stat$	Difference	$\chi^2 stat$	Difference	$\chi^2 stat$
$Neg\_News \neq Pos\_News \mid High\_Split$	0.172***	(7.23)	0.029	(0.15)	0.130**	(6.00)
N	1178945		852283		1186800	
Pseudo R2	0.163		0.166		0.162	

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, 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. $High\_Split$ is equal to 1 if the variable used for splitting is above the median, and 0 otherwise. Variable definitions for all variables are included in Appendix A and Appendix Online 1. Methodology for Twitter topics is discussed in Appendix B. The significance levels for all coefficient are denoted as follows: *** denotes $p < 0.01$, ** denotes $p < 0.05$, and * denotes $p < 0.10$. Z statistics are presented in square brackets, and χ^2 statistics are presented in parentheses.