Earnings-related activity of the S&P 500 firms on social media: An analysis of information content and audience response

Abstract:

I manually examine earnings-related Twitter activity from 2015 to 2019, for the S&P 500 firms, isolating tweets based on information content. I analyze firms' choices around when to disclose specific financial information via social media. My findings indicate that firms are less likely to disclose quantitative numerical earnings information in tweets when firm performance is below analyst expectations and more likely to disclose when performance exceeds expectations. Additionally, I test investor reactions to quantitative tweets through both Twitter follower response as well as capital market response. I find that not only is Twitter follower attention greater for tweets containing quantitative information, but that there is also a positive association with quantitative tweets and market returns as a firm's quarterly financial performance increases. Overall, my findings show that the use of Twitter is favorable for firms as value-add numerical information more likely quantifies good firm performance and yields greater reaction. However, my findings also show the ability firms have via social media to mislead investors, as firms have the discretion to limit the exposure of quantitative information when firm performance is poor.

Keywords:

Voluntary disclosure, Quantitative information, Financial information content, Social media, Twitter

I. Introduction

As of 2 April, 2013, the Securities and Exchange Commission (SEC) issued an official statement approving the use of social media outlets as a voluntary disclosure channel to report financial information, through the expansion of the Regulation Fair Disclosure, i.e., Reg FD *(SEC, 2013b)*. Following this approval, the disclosure of firm-level earnings via social media continues to increase, making Twitter the most popular social media outlet being used among companies *(Dorminey, Dull & Schaupp, 2015, Zhou, Lei, Wand, Fan & Wang, 2015 & Jung, Naughton, Tahoun & Wang, 2018)*. As of 2019, 93% of the S&P 500 companies have an official Twitter account, emphasizing not only the importance of social media among firms, but the ability firms now have to distribute information at almost no delay, to a far-reaching user-base[1].

Prior research demonstrates that firms tend to exercise strategic discretion when choosing to disseminate earnings-related announcement Twitter activity, increasing the likelihood of making an earnings-related tweet when the respective quarterly earnings meet or exceed analyst forecasts *(Jung et al. 2018)*. To further emphasize this firm-behavior, *Nebrasov, Teoh & Wu, 2021* also find firms are more likely to use visuals (i.e., images) within earnings-related tweets when financial performance is favorable.

The market effect of these tweets consistently shows a positive relationship between earnings-related tweets and capital reactions *(Blankespoor, Miller & White, 2014, Blankespoor, 2018, Jung et al., 2018 & Nebrasov, et al., 2021)*. Following the 2013 SEC ruling, capital market reactions have been growing even more positive and help highlight the impact of regulatory approval on the use of social media *(Dorminey et al., 2015)*.

[1] Upon the release of its Q1 2019 earnings report, for the first time Twitter announced its active user count at 330 million (Twitter, 2019), emphasizing the "far-reaching user-base" a firm can now exploit. See GRAPH 1 for an outline of the Twitter growth year-over-year.

While prior literature helps to explain "when" firms are more likely to make earnings-related tweets and "how" earnings tweets are made, "what" financial information firms are choosing to disclose within earnings tweets remains to be analyzed. With the rapid rise in social media being used by firms over the last decade, it is important to understand the content of the information that is being shared over this disclosure channel *(Tahoun & Wang, 2018)*. While the SEC approved the use of social media, consistent with the Reg FD initial ruling, the SEC does not currently regulate what earnings information and in what structure that information is being disclosed on social media. This provides the opportunity for management to strategically highlight certain types of information when it is advantageous to do so, thus providing the basis for my main research question: Do firm choices in disclosure content, via social media, change based on a firm's financial performance?

To address this question, I focus my paper on not only financial disclosure via social media, but also the specific information content within financial reporting. I build on *Jung et al. 2018*, which focuses on the dissemination of financial information through Twitter; i.e., when a firm makes an earnings-related tweet. I complement this and focus on the disclosure of financial earnings information through Twitter. I analyze the information being disclosed by separating earnings-related tweet content into two forms, based on prior literature. First through the use of "quantitative" information, or hard financial figures, and second through the use of "qualitative" information, or non-numerical information *(Chou, Chang, Chin & Chiang, 2018)*.

While all information, quantitative or qualitative, can be useful to investors, the level of that usefulness can vary. It is found that quantitative financial figures are more likely to be of "value-add" to investors when evaluating firm earnings and tend to garner more investor attention. As a result, quantitative information can lend itself to be used opportunistically by management *(Guindy, Naughton & Riodan, 2019, Huang, Nekrasov & Teoh, 2018, Huang, Teoh & Zhang, 2014 & Liberti & Petersen, 2019)*. When information content disclosed within

traditional financial reports is analyzed consistent results are found. *Merkley, 2014* and *Miller, 2002* observe that quantitative information disclosures are more prevalent if a firm's earnings increase quarter-over-quarter and less prevalent if earnings decrease. Conversely, qualitative information has an inverse relationship with earnings and tends to increase when performance decreases. Thus, finding firms strategically avoid reporting numerical earnings figures when it benefits management to do so. Based off of this prior literature, I therefore focus my analysis around the use of hard quantitative earnings information over qualitative information, for example: earnings per share or net income, disclosed in firm tweets.

To test this, I manually analyze all earnings-related tweets and classify each tweet by content and volume. This unique data-set allows for analysis to be performed around the specific information disclosed within each tweet. Similar to *Merkley, 2014* and *Miller, 2002,* I separate tweets with quantitative numerical earnings information from qualitative textual information. These tweets take the names "quantitative tweet" and "qualitative tweet" respectively. For an example of tweets, see APPENDIX C.

My overall results indicate that firms strategically disseminate information content via Twitter. When a firm's financial performance meets or exceeds analyst forecasts, quantitative information is significantly more likely to be disclosed in earnings-related tweets, and at a higher volume. Conversely, when financial performance falls short of expectations, quantitative information is less likely to be disclosed, and at a lower volume. This indicates that the level of discretion management exercises, via social media disclosure, is significantly dependent on the quarterly performance level of the firm. Additionally, showing strategic dissemination of quarterly value-add information, in the form of actual earnings figures (i.e., revenue, EPS, etc.), when it is of the benefit of the firm.

To further analyze the investor response to quantitative tweets, I look at both the Twitter follower response through virality metrics, as well as the capital market response through share

returns. To test the content and volume of earnings-related tweets on the Twitter audience response I calculate an "engagement rate" metric using a firm's likes and retweets. The measure shows the followers' level of engagement (i.e., interest) to the information tweeted[2]. The results indicate firms that tweet a higher volume of earnings-related tweets per quarter, especially those focused on quantitative material, have the highest overall engagement levels. Thus, quantitative tweets, made in larger volumes, attract the highest amount of audience attention.

Additionally, I measure the average engagement rate per earnings-related tweet, by taking the total engagement rate and averaging it by the number of earnings-related tweets made per firm per quarter. I find that the higher the quantity of earnings-related tweets a firm makes the less the average engagement rate becomes per tweet, with the rate dropping slower among quantitative tweets. This indicates that while an increase in earnings-related tweet volume gets a firm greater total engagement, that level of engagement dissipates the more that earnings-related tweets are made, showing interest lessens overtime. However, this dissipation is less for quantitative information showing investors in-total and on-average respond more to numerical earnings information.

These results highlight that the information firms strategically choose to disclose or not disclose, i.e., quantitative earnings figures, is the same information that firm Twitter followers appear to be the most interested in. This is in favor of the firms, as the higher level of follower engagement is more likely to occur following the release of above expected quarterly earnings. Thus, shielding the firms from bad Twitter publicity when performance is bad. However, this

[2] Twitter engagement rates are a measurement becoming popular with the rise of social media influencers and third-party social media consulting firms. The rate helps an account owner to gauge how well liked and how popular a tweet, post, or picture has become among the owner's followers. Twitter has an automated engagement rate calculation within a user's dashboard that includes additional items left out of my calculation. Because I am unable to view these items, due to not owning the firm accounts tested, I have modified the equation using information available. Please see https://help.twitter.com/en/managing-your-account/using-the-tweet-activity-dashboard for additional information on how Twitter calculates engagement rates.

favor does not extend to the firm followers. Followers will more than likely focus attention to good firm performance, as this information is more likely disclosed, and lose sight when a firm's performance is bad, as this information is less likely disclosed. This therefore has the ability to mislead investors, especially those that are non-professional *(Miller & Skinner, 2015)*.

To further understand the presentation for which quantitative information is being tweeted and ensure that the audience reaction is associated with the information content itself, I perform additional analyses around the use of visuals. *Nebrasov et al., 2021* finds a positive association between a firm's use of visuals within an earnings tweet and the Twitter user reaction. Indicating that visuals draw a greater level of Twitter attention and therefore a greater level of earnings-related attention. While *Nebrasov et al., 2021* looks at all images within earnings tweets, I test this theory by narrowing the focus to images that contain quantitative information within a tweet. More specifically, I test to see if users have a greater response to quantitative information when it is communicated via a visual or just purely within text.

I find that whether quantitative information is conveyed within an image or via text only in an earnings tweet, the overall audience attention remains consistent. This indicates that while attention fluctuates between quantitative and qualitative information, the method in which quantitative information is made does not affect how the Twitter audience responds. Thus, it appears that the actual information content within a tweet drives audience attention as opposed to the image within the tweet.

Lastly, I analyze the capital market response to quantitative tweeting activity, to test whether the market reacts in a similar way to the audience via Twitter. I calculate the three-day cumulative abnormal return (CAR) around each firm-tweet-day, one day pre tweet activity, the day of the tweet activity and the day following the tweet activity. I regress CAR on the impact quantitative tweeting has on a firm's market return, as a firm's earnings-surprise (actual EPS versus analyst forecast EPS) increases. My findings show a significantly positive

association to the interaction of earnings-surprise with the use of quantitative tweets to CAR. This indicates that a greater investor response to a firm's earnings performance occurs when firms use quantitative tweets, which is consistent with the findings around Twitter audience reactions. Quantitative earnings information appears to increase attention on both the social media platform as well as the capital market environment.

Overall, I find that due to the inherent ability for management to use discretion around the information to report via Twitter, firms tend to use this channel strategically when deciding to disclose certain information content based on financial performance for the quarter. While this behavior is favorable to firms, it has the ability to mislead investors or Twitter followers. The opportunity to mislead the audience at large is apparent with the significantly positive associations of quantitative information and response levels. These findings highlight the potential for an increase in scrutiny around the use of social media by firms and the need for further regulatory monitoring.

This paper contributes to the current social media studies around firms' use of Twitter to disseminate financial information. *Jung et al., 2018,* identifies that firm performance influences tweet timing, while *Guindy et al., 2019* indicates a change in firm tweeting patterns following the 2013 Reg FD extension. I expand on these studies by specifically identifying the firm-level earnings content disclosed, to better understand managements' disclosure inclinations on social media. Additionally, I take knowledge from the current research around quantitative versus qualitative word choice in traditional disclosure channels and expand the research through the social media disclosure channel. *Merkley, 2014 & Miller, 2002,* find management's disclosure tendencies vary between quantitative and qualitative based on firm performance. This paper finds similar results, indicating that managements' choices in reporting specific financial content appear consistent over traditional as well as voluntary disclosure channels.

The paper outline is as follows: in section II, I discuss the background of Twitter and I summarize prior literature and present my hypotheses; in section III, I explain the data collection process, summary statistics and firm-level descriptives; in section IV and V, I present my main research and additional analysis findings; I conclude the paper in section VI.

II. Background

II.1. Voluntary Disclosure & Twitter Overview

Aside from mandatory reporting requirements, publicly-traded firms also have the ability to release supplementary information to investors. This comes at the discretion of management, who can choose to provide investors with information that increases reporting transparency or information that potentially decreases transparency *(Kothari & Wysocki, 2009)*. Prior research studies the behavioral aspect of these disclosure decisions, such as: how a firm discloses financial information, when a firm discloses this information and the effects on investors *(Jung et al., 2018, Miller et al., 2015 & Kothari et al., 2009)*. Overall, the findings indicate that a firm's disclosure strategy has a direct effect on a firm's dissemination strategy, and as a result voluntarily disclosures are more likely to be made when it benefits the firm *(Jung et al., 2018, Miller et al., 2015 & Miller, 2002).*

While the decision to use voluntary disclosures resides with management, where those disclosures can be disseminated (i.e., channels) is regulated by the Securities and Exchange Commission (SEC). In August 2000, the Regulation FD (RegFD) Act was adopted to prevent selective disclosure to particular investors. RegFD requires all voluntary information be released on all disclosure channels, at the same time *(SEC, 2000)*. In July of 2012, Reed Hastings, the CEO of Netflix, challenged this act and used Facebook to disclose information regarding the financial performance of Netflix *(SEC, 2013a)*. This publicized the use of social

media as a financial disclosure channel and invoked the involvement of the SEC. On April 2, 2013, the SEC issued an official statement approving the use of social media as a disclosure channel, and as a result RegFD has been expanded to include all social media outlets *(SEC, 2013a & 2013b)*.

Since the SEC approval in 2013, the use of social media to disseminate voluntary financial disclosures is steadily increasing. Facebook and Twitter are the two most popular disclosure outlets, with Twitter exceeding Facebook in firm-level adoption rates to-date *(Jung et al., 2018 & Zhou, et al., 2015)*. Twitter offers a particularly interesting two-way platform to disclose information, opening the door for new firm-to-investor interactions *(Blankespoor, 2018)*. With Twitter having a robust level of virality metrics, as well as close to 330 million monthly users worldwide *(Twitter, 2019)*, the information a firm chooses to disclose has the ability to reach a much broader audience, at a quicker pace, when compared to other disclosure channels.

From an investor's perspective, the use of Twitter enables personal judgements on the financial information communicated in a tweet to be made public. These judgments can be actively shared through "comments" "likes" and "retweets", with the potential to positively or negatively impact a firm's reputation. This can cause adverse market effects that could have otherwise been avoided if Twitter was not used *(Miller & Skinner, 2015)*. Conversely, from a firm perspective, the SEC approval has lifted the uncertainty around social media use, giving firms the discretion to freely share information. Firm behavior is shifting, with financial tweets now containing more specific earnings information as opposed to generic information *(Guindy et al., 2019)*. This change in disclosure is two-sided. On one side it shows that firms believe "value-relevant" information can now securely be shared via Twitter *(Guindy et al., 2019)*, thus potentially increasing transparency. On the other side, it gives firms the ability to strategically

disseminate information when firm performance is favorable/unfavorable *(Jung et al., 2018),* thus potentially decreasing transparency.

Overall, while the use of social media has only recently been adopted as a financial disclosure channel, the adoption has created a unique setting for further research. The two-way structure of Twitter allows firms to exercise a new level of management discretion, as well as investors to exercise a new level of public opinion. Both helping to create a new level of firm-investor interaction.

II.2. Literature Review & Hypotheses

Prior studies have examined the behavioral choices firms make when disclosing information, via social media, as well as the associated investor response. *Jung et al., 2018* emphasize that while the disclosure (of) and dissemination of information are two different acts, what influences a firm's disclosure level may also influence a firm's dissemination level. This dissemination level can provide more timely transparent disclosures to a larger audience *(Blankespoor et al., 2014),* or can be used strategically, having the opposite effect. Disseminating information when the news is "good" and not disseminating information when the news is "bad", can potentially mislead investors, particularly those that are non-professional *(Jung et al., 2018 & Miller & Skinner, 2015).*

With the rise of social media over the past decade, the use of this outlet as a financial disclosure channel continues to grow with firm behavioral choices evolving. Since the inception of Twitter, capital market responses to the release of financial information via Twitter are positive. A financial tweet is associated with higher market liquidity and lower information asymmetry *(Blankespoor et al., 2014),* which only gets stronger the more followers a firm's Twitter account has *(Jung et al., 2018).* These market reactions are also similar for CEO and

individual tweets, finding positive relationships with information asymmetry *(Bartov, Faurel & Mohanram, 2018 & Elliott, Grant & Hodge, 2018)*. While these effects positively benefit firms, the use of Twitter also can have the ability to mislead investors, especially if those investors are less informed *(Miller & Skinner, 2015)*. Criticism of firms' financial disclosure via the use of virality metrics, show that non-professional investors' perception of that firm's reputation can be harmed *(Cade, 2018)*. Additionally, as the financial information being disclosed spreads further from the original source (i.e., the firm), the more information asymmetry in the market grows *(Jung et al., 2018)*.

Following the 2013 SEC approval, the market responses to Twitter are increasing. *Dorminey et al., 2015* finds that trading volume, in reaction to financially-related tweets after the 2013 ruling have grown. This indicates that Twitter disclosures most likely reach a wider base and are more likely deemed reliable by investors. Additionally, when stock price responses are analyzed, there is a statistically significant positive increase of 25 basis points following the 2013 SEC approval *(Guindy, et al., 2019)*. This indicates the increasing impact of Twitter on market reliance and even more so following regulatory approval.

Conversely, the analysis around firm-level tweeting behavior, unlike market responses, yield mixed results. *Jung et al., 2018* finds firms strategically disseminate earnings via Twitter based on financial performance. When earnings fall short of expectations, the likelihood of a firm tweeting decreases, showing the firm's attempt to use Twitter as an opportunistic dissemination channel. However, tweet activity also shows that firms no longer decide to initially tweet financial information based on performance, indicating that firms are equally as likely to use Twitter when earnings fall short as well as exceed expectations *(Crowley et al., 2020)*. This demonstrates that as the use of Twitter rises over the years, the decisions for which firms choose (or choose not to) when to use social media continues to evolve.

While firm-level analysis shows "when" firms disseminate earnings-related information via Twitter, the specifics around "what" actual earnings content firms choose to tweet, remains largely unanalyzed. *Nekrasov, et. al., 2021* finds that firms are marginally less likely to use a visual (or image) within earnings-related tweets, as visuals draw additional user attention. However, understanding whether the visual or the content of that visual drives firm tweeting behavior is unknown.

To classify disclosure information within earnings-related information *Liberti et al., 2019*, labels information content as either "hard" or "soft". Hard information is quantitative earnings numbers, such as earnings per share (EPS) or revenue, whereas soft information is qualitative in nature, or textually descriptive. Prior research finds that not only is quantitative information considered a "value-add" to reporting, but that quantitative figures also tend to attract greater investor attention (*Huang et. al., 2014*). Additionally, as management discretion plays a substantial role in reporting choices, studies find that firms are more likely to disclose quantitative information in the presence of good financial performance, with the volume of quantitative content increasing as the performance increases, via traditional disclosures *(Chou et al., 2018; Liberti et al., 2019 & Merkley, 2014 & Miller, 2002)*[3]. Firms are also more likely to use quantitative earnings figures to headline earnings announcements when performance is favorable, furthering the strategic use of quantitative reporting (*Huang et. al., 2018*).

In this paper, I focus my studies around firm incentives (or lack thereof) to tweet specific earnings information content, mainly quantitative content, based on the classifications of *Liberti et al., 2019.* As management shows signs of using this content strategically, I assume that similar to traditional disclosure channels, firm performance will help to dictate Twitter

[3] *Miller, 2002* evaluates financial reporting disclosures using six sub-categories: earnings announcements, earnings and sales forecasts, earnings preannouncements, information regarding operations, dividend-related information and miscellaneous disclosures. Whereas, *Merkley, 2012*, focuses on disclosures covering Research and Development (R&D).

disclosure. Also, as prior literature indicates that quantitative information is more "value-add" to investors, I assume that the response to this information will be stronger via Twitter than qualitative information. As such, the following are my two main hypotheses:

H1: If firms use Twitter to disclose earnings-related information, they are less likely to release quantitative earnings figures, when financial performance is below analyst expectation.

H2: When firms use Twitter to disclose earnings-related information, the audience response is stronger for quantitative earnings figures.

III. Sample & Data

I start with all S&P 500 firms as of March 31, 2019, obtained from Compustat, as this is the ending time period of my sample. To identify which firms within the S&P 500 have a "company-maintained" Twitter account I perform three steps to hand-collect the data. First, I manually search the Twitter application for a verified[4] company Twitter account, indicating Twitter has confirmed the handle owner as the S&P 500 firm itself. Second, if no verified account exists, I visit the official corporate website of the firm and search for an embedded Twitter link, for which I click and get redirected to that firm's Twitter handle. Third, if no Twitter link exists, I manually search Twitter for a handle that represents the firm, has a link to the official corporate website on the handle's homepage, and/or states the handle to be "the official account of …" for the associated S&P 500 firm. These three steps mirror prior literature and give assurance that all S&P 500 firm Twitter accounts are identified and are appropriately included in the sample *(Jung et al., 2018)*. In addition to gathering the Twitter accounts, I also

[4] A verified account on Twitter is indicated by the blue verified badge next to the Twitter handle, which confirms an account to be authentic. The badges are applied only by Twitter itself and can be obtained by users in key areas of interest including businesses (Twitter, n.d.).

obtain the inception date and virality metrics[5] of those accounts, which are hand-collected directly from the Twitter website[6].

III.1. Overall Twitter Activity

I find that as of 2019 93% or 463 firms out of the 500 firms that compile the S&P 500 have company-owned Twitter accounts. Year-over-year adoption analysis shows that starting in 2015 the firm adoption rate begins to level off, growing only 1 to 2% year-over-year until 2019. See GRAPH 1 for additional details. Paralleling the adoption rates, the number of Twitter followers is also leveling off, growing at virtually 0% year-over-year since 2012. Consistent with *Zhou et al., 2015*, these leveling off results indicate that most likely all S&P 500 firms that have not yet adopted Twitter will continue to not do so in the future. Conversely, those users that are not yet following a Twitter account will also continue to not do so in the future.

INSERT HERE GRAPH 1

III.2. Earnings-announcement Firm Twitter Activity

As my analysis finds 2015 to be the year Twitter growth begins to stabilize, I determine tweet activity related to quarterly earnings from calendar period Q1 2015 through Q4 2018 as my population for testing. The tweet activity is obtained through the Twitter Application

[5] The virality metrics collected include the total number of followers, tweet activity, and likes.

[6] The hand-collection was done over a two-week time period, from the last week in March through the first week in April 2019. The data obtained is only observable at a point in time and changes as account activity occurs. This therefore creates a limitation on the ability to collect virality metrics as of an exact date and time for all firms.

Program Interface (API)[7], a development arm of Twitter which is maintained and monitored directly by the company. The tweeting data is pulled using Twitter initiated coding and is migrated into R for further analysis.

To accurately identify earnings-related tweets within the population I filter for tweets containing financial keywords from the word listing in APPENDIX B[8]. The listing builds off of *Jung et al., 2018* with additional words added to ensure all appropriate tweets are identified. Furthermore, I obtain the quarterly earnings release dates from Compustat for each firm, to isolate only the tweets posted in a 10-day pre-and-post period from those dates, similar to prior research *(Jung et al., 2018)*. As voluntary disclosures made via social media cannot be treated preferentially compared to other channels, it is reasonable to assume earnings tweets would not take place more than 10 days before a firm officially releases the quarterly press release.

I manually classify the earnings-related tweets by two factors: tweet content and tweet volume. Tweet content refers to hard/quantitative versus soft/qualitative information as defined by *Chou et al. 2018* and *Liberti et al., 2019.* Tweet volume is the total count of earnings-related tweets made per firm per quarter. Following prior research on earnings disclosure *(Miller, 2002)*, I isolate all earnings-related tweets containing quantitative figures. These tweets will be called "quantitative tweets" throughout the paper. All remaining tweets containing solely soft information I classify as "qualitative tweets".

Quantitative tweets are the primary focus of tweet content as this information is perceived to be more useful content for an investor (*Huang et. al., 2018 & Huang et. al., 2014*). Furthermore, quantitative information shows investors actual hard earnings figures, which can then be used for further analyses. As specific information released on Twitter is the sole discretion of management, if firms are choosing to not disclose value-added information (i.e.,

[7] For additional information around the Twitter API see: https://developer.twitter.com/

[8] The list of keywords is systematically filtered through the tweet population using STATA.

quantitative information) based on financial performance, this could be a signal that Twitter is being used to strategically disclose earnings information.

To classify tweet volume, I take the total number of earnings-related tweets made per firm per quarter for all earnings-related tweets regardless of the content, for quantitative earnings tweets and for qualitative earnings tweets. Overall, tweet shows whether firms choose to emphasize certain quarterly earnings content more times or less based on financial performance. For examples of tweet classifications see APPENDIX C.

In total, the Twitter activity population yields 279,667 tweets, from the 463 S&P 500 firms. Upon review, I obtain a final sample size of 2,874 total earnings-related tweets made within the sample period, yielding a total of 1,009 unique firm-quarters[9]. The earnings-related tweets are made by 98 firms (or 20% of the S&P 500), representing 1.0% of the total Twitter population, consistent with prior findings *(Zhou et al., 2015)*[10]. See TABLE 1: Panel A for further details.

GRAPH 2 displays the breakout of tweet volume by content. The results indicate that the total number of firms that tweet quantitative earnings fluctuate only slightly per quarter. At first thought this may indicate consistent quarter over quarter tweeting behavior from firms; however, upon analyzing the consistency around the unique volume of firms making the earnings tweets, patterns emerge showing that firms do not uniformly make quantitative earnings tweets from quarter to quarter. GRAPH 3 shows a summary of yearly firm activity. The graph indicates that on average, of the firms that tweet quantitatively, those firms only tweet 35% to 41% of the quarters throughout a given year. This is compared to firms that make

[9] As quarterly earnings are reported to investors in the proceeding calendar quarter, the final sample used for analysis is the 16 calendar quarters from Q1 2015 to Q4 2018. All fiscal quarters are converted to calendar quarters to be consistent across firms. As the Twitter population obtained is through 31.3.2019, this ensures ample time for all Q4 2018 firm results to be released.

[10] All 98 firms' Twitter accounts have inception dates prior to 2015, when the sample starts.

qualitative tweets, which on average firms make these tweets 58% to 63% of the quarters in a year. The gap of approximately 20%-30% between quantitative versus qualitative tweeting behavior shows that of the firms choosing to use Twitter, qualitative tweets are released on a more consistent basis, whereas quantitative tweets tend to be more inconsistent.

INSERT GRAPH 2 HERE

INSERT GRAPH 3 HERE

GRAPH 4 further breaks down firm tweeting pattern consistency on a more detailed level (quarter over quarter), showing that not only do firms pick-and-choose when to tweet specific earnings information content, but that the fluctuation of unique firms that tweet quarter-over-quarter varies greater for quantitative tweets than qualitative tweets. Between 5% to 38% of additional unique firms tweet quantitative information in the current quarter without having made a tweet with the same content (i.e., quantitative or qualitative) in the previous quarter. This is compared to between 4% to only 18% for qualitative tweets. Consistent with GRAPH 3, this indicates that more firms tweet quantitative information sporadically.

Overall, graphs 2, 3 and 4 show that while the total volume of firms tweeting remain relatively consistent in total, the firms' tweeting behavior vary distinctively for quantitative versus qualitative tweeting. These patterns help to illustrate the potential for firm "cherry-picking" around when to tweet "value add" hard earnings information. Possibly limiting the quantitative content investors see via Twitter when earnings are bad and expanding the content when earnings are good.

INSERT GRAPH 4 HERE

III.3. Earnings-announcement Firm Industry Activity

TABLE 1: Panel B breaks out the tweeting activity by industry using the Fama-French 10 industry classifications[11], showing that firm-level earnings-related tweeting patterns vary by industry and by quarter, consistent with prior research *(Jung et al., 2018 & Nekrasov, et al., 2021)*. The top three highest quantitative tweeting industries are Consumer Durables (i.e., food), Wholesale & Retail and Others (i.e., travel, entertainment as well as financial firms). While variation exists among the firms, it is important to note that no one industry dominates in either quantitative tweeting volume or total earnings tweeting volume.

INSERT TABLE 1 HERE

III.4. Descriptive Analysis

To analyze what factors contribute to a firm making earnings-related tweets during a given quarter, I gather firm characteristic variables focusing on financial performance, media, analyst and Twitter follower presence, as well as the age of the firm for each quarter. I use the firm variables identified in *Crowley et. al., 2020, Jung et al., 2018* and *Nekrasov, et al, 2021* as a basis for my framework.

The main Twitter-Activity variables of interest are as follows: QUANT_QTR, a binary variable of 1 if a firm made one quantitative tweet within the quarter and 0 otherwise; QUAL_QTR, a binary variable of 1 if a firm made one qualitative tweet within the quarter and 0 otherwise; TWEET_VOLUME_TOTAL, a continuous variable of the number of all earnings-related tweets made by a firm in a quarter; TWEET_VOLUME_QUANT, a

[11] This classification is also used when controlling for industry fixed effects in the main analyses.

continuous variable of the number of tweets made by a firm in a quarter that contain a quantitative earnings figure; and TWEET_VOLUME_QUAL, a continuous variable of the number of tweets made by a firm in a quarter that contain only qualitative information, no quantitative figures. Additionally, the main Twitter-Response variables of interest are as follows: TOTAL_ENGAGE_RATE, a continuous variable indicating the total overall audience response to a firm's quarterly earnings tweets; and AVG_ENGAGE_RATE, a continuous variable indicating the average audience response to a firm's quarterly earnings tweets.

Firm characteristic variables include MISSFORECAST, a binary variable set to 1 (or 0 otherwise) if a firm's actual earnings per share (EPS) did not meet or exceed the firm's analyst forecasted EPS for that quarter. SALES_GROWTH, a continuous variable measuring the difference between the current quarter's sales revenue and the same quarter's revenue from the prior year. SIZE, a continuous variable of the firm's asset level per quarter. LEV, a continuous variable measuring the firm's debt to asset percentage for the quarter. ROA, a continuous variable measuring the firm's return on assets for the quarter. MTB, a continuous variable measuring the firm's market to book value percentage for the quarter. MEDIA_NEWS, a continuous variable measuring the amount of earnings-related outside news articles issued for the quarter proceeding the fiscal quarter. PRESS_RELEASES, a continuous variable measuring the amount of earnings-related press releases issued by the firm for the quarter proceeding the fiscal quarter. ANALYSTS, a continuous variable measuring the number of outside analysts following a firm in the quarter. FOLLOWERS, a continuous variable measuring the number of Twitter followers of each firm in the quarter. FIRM_AGE, an integer variable measuring the age of the firm for each quarter.

TABLE 2 shows the descriptive statistics for both the Twitter-related variables as well as the firm-related variables. The mean of TWEET_VOLUME_TOTAL is 1.123. Prior to standardization of the variables, this indicates that on average there are 2.85 earnings-related

tweets in total by firm, per quarter. Of the 2.85 total tweets, approximately 0.75 are quantitative tweets (TWEET_VOLUME_QUANT mean of 0.339), and approximately 2.10 are qualitative tweets (TWEET_VOLUME_QUAL mean of 0.95). QUANT_QTR has a mean of 32.7, indicating that 32.7% of firm quarters have quantitative tweeting activity. As for firm performance, the mean for MISSFORECAST is 0.174. This indicates that 17.4% of firm quarters missed analyst forecast earnings. Additionally, the average growth in sales from current quarter to prior year quarter is 4.2%.

INSERT TABLE 2 HERE

IV. Main Results

IV.1. Earnings-announcement Tweet Analysis by Volume & Content

In this section I test hypotheses H1, analyzing the content and volume of earnings-related tweets. *Jung et. al., 2018* finds that firms strategically disseminate earnings tweets based on financial performance; however, the information content that firms tweet have yet to be analyzed. This forms the basis for my main research question: Do firm choices in disclosure content, via Twitter, change based on financial performance?

To test the above, I use Probit and OLS regressions to examine this. The regression equation is as follows:

$$TWEET_{iq} = \beta_0 + \beta_1 MISSFORECAST_{iq} + \beta_2 SALES_GROWTH_{iq} + \beta_3 SIZE_{iq} + \beta_4 ROA_{iq} + \beta_5 MTB_{iq} + \beta_6 MEDIA_NEWS_{iq} + \beta_7 PRESS_RELEASES_{iq} + \beta_8 ANALYSTS_{iq} + \beta_9 FOLLOWERS_{iq} + \beta_{10} FIRM_AGE_{iq} + INDUSTRY\ FIXED\ EFFECTS + FIRM\ FIXED\ EFFECTS + QUARTER\ FIXED\ EFFECTS + YEAR\ FIXED\ EFFECTS + \varepsilon_{iq} \quad (1)$$

All control variables remain consistent as in the previous section, with the determinant variable MISSFORECAST becoming the intended independent variable of interest, as it is the main indicator for firm performance. TWEET proxies for three different dependent variables: TWEET_VOLUME_TOTAL, TWEET_VOLUME_QUANT and TWEET_VOLUME_QUAL. I further include industry fixed effects based on the Fama-French 10, as well as firm fixed effects, quarter / year fixed effects based on calendar quarters, and winsorized continuous variables at the 1^{st} and 99^{th} percentiles. For additional variable calculation explanation please refer to APPENDIX A.

The main results are displayed in TABLE 4. Overall, I find that based on tweeting behavior patterns, firms are significantly less likely to tweet numerical (quantitative) earnings information when firm performance does not meet expectations (MISSFORECAST) across and within firms. This indicates strategic disclosure on behalf of firms, not around the timing of the tweet, but instead based on the content within the tweet.

In column 1 and 2, TWEET_VOLUME_TOTAL has a significantly negative MISSFORECAST coefficient of -0.0915 (p-value <0.05) and -0.0419 (p-value<0.10) respectively, indicating when all earnings-related tweet volume, regardless of content, is included firms are less likely to tweet when performance is below expectation.

When I focus on the specific tweet content for all earnings-related tweets columns 3 and 4 outline firm-behavior as it relates to quantitative tweeting activity. TWEET_VOLUME_QUANT has a significantly negative MISSFORECAST coefficient of -0.0982 (p-value <0.05) and -0.0508 (p-value<0.05) respectively. These results show that firms are significantly less likely to choose to make a quantitative tweet and continue to make subsequent quantitative tweets in that same quarter when EPS is below expectation and sales growth is lower than prior year quarter. Tweeting patterns around the volume of quantitative tweets remains significant for both across firm and within firm settings.

In columns 5 and 6 TWEET_VOLUME_QUAL have no significance as it relates to MISSFORECAST. The lack of significance indicates that unlike quantitative tweeting, firm financial performance does not appear to be a main driver for qualitative tweeting.

These results show that while overall firms are significantly less likely to tweet in general when performance is below expectation, the significance appears to be when firms decide to tweet (or not tweet) quantitative earnings information, not qualitative information. Further, firms appear to "cherry-pick" when more "value-add" information is tweeted to firm followers based on more favorable financial performance.

Apart from the MISSFORECAST results, I find that quantitative tweets are more likely associated with larger firms (SIZE), firms with higher market to book values (MTB), and firms with more Twitter followers. These findings are fairly consistent with prior literature (*Jung et al., 2018*). It is important to note that while I follow previous regression models regarding the use of social media (*Crowley et. al., 2020, Jung et al., 2018 & Nekrasov, et al, 202*) it appears that the use of qualitative tweets for the most part does not garner significance around the remaining control variables.

In total, my results show an underlying pattern of strategic disclosure based on firm performance. The results indicate that quarterly earnings and sales help to drive the content and volume of content that is disclosed in an earnings-related tweet. My analysis helps to confirm hypothesis H1 to varying significance. This indicates firms are less likely to release hard earnings information when financial performance is below analyst expectation. This result further extends the findings of *Merkley, 2014 & Miller 2002*.

INSERT TABLE 4 HERE

IV.2. Audience Reaction Analysis to Earnings-announcement Tweets

In this section I test hypothesis H2. As it shows above, firms strategically disclose certain information via Twitter, presumably to influence that corresponding firm's Twitter followers (i.e., audience). Understanding how the audience then reacts to the released information is vital, especially as the level of earnings-related tweets made by firms becomes more prevalent. In this section I analyze the overall audience reaction following the firms' quarterly earnings-related tweets release. Twitter allows users to express opinions through virality metrics or the enactment of "retweets" and "likes". Retweets enable tweets to spread outside of a firm's immediate follower network and into a wider audience base. Likes enable firms to see which tweets were the most favorite to view by followers. Both metrics have the ability to influence followers and firms, in both positive and negative ways.

To measure the audience reaction, I start by calculating a firm's "engagement rate" per quarter for all earnings-related tweets a firm makes. The engagement rate is a measurement equation I create which incorporates both retweets and likes for completeness. Additionally, I split the equation into two parts to first get the total engagement rate for all earnings-related tweet activity by a firm in each quarter, and then to second get the average engagement rate per earnings-related tweet by a firm in a quarter. The calculations are as follows:

$$TOTAL_ENGAGE_RATE_{iq} = log\ (1 + TOTAL_LIKES_{iq} + TOTAL_RETWEETS_{iq}) \quad (2)$$

$$AVG_ENGAGE_RATE_{iq} = TOTAL_ENGAGE_RATE_{iq} / NUM_EA_TWEET_{iq} \quad (3)$$

To test the audience reaction, I use cross-sectional OLS regressions to examine this:

$$\begin{aligned} ENGAGE_RATE_{iq} =& \beta_0 + \beta_1 TWEET_VOLUME_TOTAL_{iq} + \\ & \beta_2 TWEET_VOLUME_QUANT_{iq} + \beta_3 TWEET_VOLUME_QUAL_{iq} + \beta_4 MISSFORECAST_{iq} \\ & + \beta_5 SALES_GROWTH_{iq} + \beta_6 SIZE_{iq} + \beta_7 ROA_{iq} + \beta_8 MTB_{iq} + \beta_9 MEDIA_NEWS_{iq} + \\ & \beta_{10} PRESS_RELEASES_{iq} + \beta_{11} ANALYSTS_{iq} + \beta_{12} FOLLOWERS_{iq} + \beta_{13} FIRM_AGE_{iq} + \\ & FIRM\ FIXED\ EFFECTS + QUARTER\ FIXED\ EFFECTS + YEAR\ FIXED\ EFFECTS + \\ & \varepsilon_{iq} \end{aligned} \quad (4)$$

ENGAGE_RATE proxies for the following two dependent variables: TOTAL_ENGAGE_RATE and AVG_ENGAGE_RATE. TOTAL_ENGAGE_RATE is a continuous variable indicating the total likes and retweets per firm-quarter. AVG_ENGAGE_RATE is a continuous variable indicating the average likes and retweets per EA tweet per firm quarter. All control variables remain consistent as explained in the Descriptive Analysis section. I add TWEET_VOLUME_TOTAL, TWEET_VOLUME_QUANT and TWEET_VOLUME_QUAL, as variables of interest to evaluate the impact of total tweet volume and total tweet content on engagement rates.

The results are displayed in TABLE 5 on a firm over time level[12]. The analysis in column 1 of a firm's total engagement rate per quarter shows a highly significant positive relationship between the total volume of earnings-related tweets (TWEET_VOLUME_TOTAL) and the total engagement rate (TOTAL_ENGAGE_RATE). In column 2, I breakout the earnings-related tweets by content: quantitative and qualitative. The results also find significant positive coefficients for both TWEET_VOLUME_QUANT and TWEET_VOLUME_QUAL, indicating that the more a firm tweets the more retweets and likes a firm receives (in total).

When looking at the coefficients, TWEET_VOLUME_TOTAL to engagement rate increase is 0.768 (p-value<0.01). As for quantitative and qualitative tweets, both have positive coefficients; however, TWEET_VOLUME_QUANT appears to drive a slightly greater majority of the total engagement rate increase with a coefficient of 0.590 (p-value<0.01), while TWEET_VOLUME_QUAL has a coefficient of 0.476 (p-value<0.01). This indicates that followers respond more to tweets with numerical earnings figures (quantitative) than soft non-numerical text (qualitative). Additionally, it is important to note that MISSFORECAST has no

[12] TABLE 5 results are also consistent when Industry fixed effects are included. As it can be assumed that followers on Twitter continue to follower the same accounts on Twitter over-time, Firm fixed effects are the focus of this analysis.

significance, showing followers do not respond to an increase or decrease in a firm's performance level, consistent with prior literature *(Jung et al., 2018).* However, followers do respond significantly positive when SALES_GROWTH increases with a coefficient of 0.389 (p-value <0.05). This result can potentially be attributed to more non-professional Twitter users having access to quarterly reports distributed by firms that show past sales figures, which might sway followers to like/retweet more or less depending on performance. Analyst forecasts could be harder for non-professional users to obtain, therefore putting more emphasis on sales growth.

When I analyze firms' average tweet engagement rate, adverse results are found. In column 3, the results indicate there is a significantly negative coefficient related to TWEET_VOLUME_TOTAL. This shows that as total earnings-related tweet volume increases, the average number of retweets and likes received (i.e., engagement rate) per tweet actually decreases, with a coefficient of -1.535 (p-value<0.01). The results are consistent in column 4 as well, with the split of quantitative and qualitative tweets both having significantly negative coefficients. However, the results find that on average the engagement rate per tweet appears to decrease the quickest for qualitative tweets with a coefficient of -1.280 (p-value<0.1), followed by quantitative tweets of -0.624 (p-value<0.01). This indicates, similar to the TOTAL_ENGAGE_RATE results, that followers are more engaged with quantitative information, and with the lower coefficient value, tend to lose interest in quantitative tweets slower than qualitative tweets. Moreover, as is expected, overall engagement rates are positively significantly associated by a firm's size (SIZE), a firm's market-value (MTB) and a firm's follower level (FOLLOWERS). The engagement rates are negatively associated with a firm's level of press releases issued within a quarter (PRESS_RELEASES) as well as a firm's age (FIRM_AGE). These results indicate that the larger, more valuable the firm, the more attention that firm's Twitter account receives.

Overall, the results show that not only does earnings-related tweet volume directly effect a firm's level of audience engagement, but that the content within the tweet volume helps to drive this effect. With audience attention growing greater as the volume of quantitative tweets increases, as well as that attention being maintained over a longer period of time, it can be assumed that quantitative tweets are of more interest to the Twitter audience than qualitative tweets. This is to be expected as hard information is seen as a "value-add", especially for investors *(Guindy et al., 2018, Huang et al., 2018 & Haung et al., 2014)*.

These findings, along with the findings in the section above, indicate that firms are more likely to disclose quantitative tweets with good firm performance, and that those quantitative tweets are more likely to garner the most engagement from followers. Thus, most likely shifting follower attention to positive disclosures and away from negative disclosures, with the potential to mislead investors, especially those that are non-professional *(Miller et al., 2015)*.

INSERT TABLE 5 HERE

V. Additional Analyses

V.1. Audience Reaction Analysis to Quantitative text versus Visuals

In this section I build off of *Nekrasov, et al., 2021* who find a positive association between a firm's use of visuals (i.e., images) within an earnings tweet and the Twitter user reaction. *Nekrasov, et al., 2021* argues that the underlying theory driving these results is the "Visual Attention Hypothesis", which indicates that the use of visuals draws greater attention to tweet activity and therefore greater attention to a firm's earnings news and a higher associated Twitter as well as market reaction. While *Nekrasov, et al., 2021* looks at all images within earnings-

related tweets, I test this theory further by focusing on not only the images within tweets but images that contain quantitative earnings content within tweets. More specifically, I test to see if the results of greater reaction to visuals found in *Nekrasov, et al., 2021* is related to the use of visuals or if it is actually the content within the visuals that drive the increase in attention.

To test this I introduce two additional variables: TWEET_VOLUME_VISUAL_QUANT, which is a continuous variable of the number of quantitative tweets that have images within the tweet which contain the quantitative information, and TWEET_VOLUME_NON_VISUAL_QUANT, which is a continuous variable of the number of quantitative tweets that do not have images within the tweet.

I run Probit and OLS regressions using the following equation:

$$TWEET_VOLUME_VISUAL_QUANT_{iq} = \beta_0 + \beta_1 MISSFORECAST_{iq} + \beta_2 SALES_GROWTH_{iq} + \beta_3 SIZE_{iq} + \beta_4 ROA_{iq} + \beta_5 MTB_{iq} + \beta_6 MEDIA_NEWS_{iq} + \beta_7 PRESS_RELEASES_{iq} + \beta_8 ANALYSTS_{iq} + \beta_9 FOLLOWERS_{iq} + \beta_{10} FIRM_AGE_{iq} + INDUSTRY\ FIXED\ EFFECTS + FIRM\ FIXED\ EFFECTS + QUARTER\ FIXED\ EFFECTS + YEAR\ FIXED\ EFFECTS + \varepsilon_{iq} \quad (5)$$

The results are displayed in TABLE 6. The analysis in column 1 the analysis shows that of the volume of visual quantitative tweets (TWEET_VOLUME_VISUAL_QUANT) made by firm per quarter shows a further significant negative relationship to MISSFORECAST (coefficient of -0.0689 p-value<0.05). These results indicate that similar to the results in my main analysis, firms are also less likely to tweet quantitative information within visuals when financial performance is below expectation across firms[13].

[13] No significance on MISSFORECAST is found when industry fixed effects are replaced with firm fixed effects. This most likely can be attributed to the relatively low rate of additional unique firms making quantitative visual tweets year over year, between 6% to 8% of total tweeting firms. Visuals appear to be tweeted by a consistent level of firms within my sample period, and thus variation is most likely limited.

INSERT TABLE 6 HERE

As quantitative visuals appear to be used in the same manner as quantitative information in general from TABLE 4, I further test the audience reaction related to the different methods in which quantitative figures can be displayed within a tweet. I do this by splitting out the quantitative tweet volume per firm per quarter in my main analysis by quantitative tweets that do not have an image within the tweet (purely textual and numerical), TWEET_VOLUME_NON_VISUAL_QUANT and by quantitative tweets that have an image, TWEET_VOLUME_VISUAL_QUANT.

I run Probit and OLS regressions using the following equation:

$$\begin{aligned} ENGAGE_RATE_{iq} = {} & \beta_0 + \beta_1 TWEET_VOLUME_VISUAL_QUANT_{iq} + \\ & \beta_2 TWEET_VOLUME_NON_VISUAL_QUANT_{iq} + \beta_3 TWEET_VOLUME_QUAL_{iq} + \\ & \beta_4 MISSFORECAST_{iq} + \beta_5 SALES_GROWTH_{iq} + \beta_6 SIZE_{iq} + \beta_7 ROA_{iq} + \beta_8 MTB_{iq} + \\ & \beta_9 MEDIA_NEWS_{iq} + \beta_{10} PRESS_RELEASES_{iq} + \beta_{11} ANALYSTS_{iq} + \beta_{12} FOLLOWERS_{iq} + \\ & \beta_{13} FIRM_AGE_{iq} + FIRM\ FIXED\ EFFECTS + QUARTER\ FIXED\ EFFECTS + YEAR \\ & FIXED\ EFFECTS + \varepsilon_{iq} \end{aligned} \quad (6)$$

ENGAGE_RATE is a proxy for both the total engagement rate as well as the average engagement rate. The results are displayed in TABLE 7. Similar to the results in my main analysis, both quantitative tweets with visuals as well as without visuals garner significant attention from the audience in comparison to qualitative tweets. However, both the quantitative visual tweets and the non-visual tweets have similar coefficients as each other. TWEET_VOLUME_VISUAL_QUANT and TWEET_VOLUME_NON_VISUAL_QUANT coefficients for TOTAL_ENGAGE_RATE is 0.464 (p-value <0.01) and 0.473 (p-value <0.01) respectively. For AVG_ENGAGE_RATE, TWEET_VOLUME_VISUAL_QUANT and TWEET_VOLUME_NON_VISUAL_QUANT coefficients are -0.480 (p-value <0.01) and -

0.574 (p-value <0.01) respectively. This indicates that while the presentation of quantitative tweets can vary, visuals versus no visuals, the mean change in the total and average engagement rates for each additional tweet remains relatively consistent to one another.

Overall, these results show that when quantitative information content is conveyed with a visual or without a visual, the audience attention level remains constant. Quantitative tweets without visuals have a slightly higher impact on the total engagement rate for the quarter, while the quantitative tweets with visuals have a slightly higher impact on the average engagement rate for the quarter. This helps to show that the Twitter audience in general reacts different when seeing quantitative versus qualitative information, but not different when seeing quantitative information in images and without images. Thus, it appears engagement rates are driven by the actual information content within an earnings tweet as opposed to how that information is presented.

INSERT TABLE 7 HERE

V.2. Capital Market Reactions to Quantitative Tweeting

Nekrasov et al., 2021 find that firms are more likely to tweet visuals in earnings-related tweets when firm-level performance is better than analyst expectation. Based on my findings this appears consistent with the use of quantitative information within earnings tweets as well. *Nekrasov et al., 2021* also finds that there is a significant positive association with the tweeting of visuals on the market return. As quantitative information patterns are similar to visual patterns, I test whether quantitative information has the same effect on capital markets as visuals do.

To analyze the investor response of quantitative information on a firm's financial performance relative to the market return, I use *Nebkrsov et al., 2021* as a baseline for my regression equation. The following probit and OLS regressions are run:

$$CAR_{i,t-1,t,t+1} = \beta_0 + \beta_1 EARN_SURP_{iq} * QUANT_{it} + \beta_2 SALES_SURP_{iq} * QUANT_{it} + \beta_3 SIZE_{iq} * QUANT_{it} + \beta_4 ROA_{iq} * QUANT_{it} + \beta_5 MTB_{iq} * QUANT_{it} + \beta_6 MEDIA_NEWS_{iq} * QUANT_{it} + \beta_7 PRESS_RELEASES_{iq} * QUANT_{it} + \beta_8 ANALYSTS_{iq} * QUANT_{it} + \beta_9 FOLLOWERS_{iq} * QUANT_{it} + \beta_{10} FIRM_AGE_{iq} * QUANT_{it} + FIRM\ FIXED\ EFFECTS + QUARTER\ FIXED\ EFFECTS + YEAR\ FIXED\ EFFECTS + \varepsilon_{iq} \quad (7)$$

CAR is the dependent variable with takes the value of the cumulative adnormal return of a firm's share price starting from the day prior, day of and day following a day when an earnings-related tweet is made. The abnormal return is calculated by subtracting the predicted firm return from the estimation period from the actual daily firm return. The main variable of interest is EARN_SURP which is a decile ranked value of the difference between the actual EPS and the analyst forecasted EPS interacted with QUANT. QUANT is a proxy for two variables: QUANT_DAY which is a binary variable that is equal to 1 if the firm makes a quantitative tweet on that firm day, or 0 otherwise, and TWEET_VOLUME_QUANT_DAY which is a continuous variable measuring the volume of quantitative tweets made on a firm day. The remainder of control variables are also interacted with QUANT to measure the effect of quantitative information on each.

TABLE 8 shows the results of regressions. In column 1 CAR shows a significantly positive relationship with EARN_SURP interacted with QUANT_DAY, indicating that the level of investor response when a firm's earnings performance increases, grows when a firm makes a quantitative tweet (coefficient 0.001 p-value >0.05). The same results are also present when EARN_SURP is interacted with TWEET_VOLUME_QUANT_DAY (coefficient 0.001 p-value >0.05). This indicates that as a firm's earnings performance increases the effect that

tweeting quantitative information (and in higher volumes) has on a firm's cumulative abnormal return is positive.

Additionally, quantitative tweets show to have a significant positive effect on ROA and a marginally significant negative relationship on MTB. The variables QUANT_DAY as well as TWEET_VOLUME_QUANT_DAY both have marginally and highly significant negative relationships to CAR, respectively, without interaction terms. This is to be expected as more firms tweet qualitatively and the firms that do tweet quantitatively do so selectively. As a robustness check to address endogeneity around firms that use and do not use quantitative information via Twitter, I also follow *Nekrasov et al., 2021* and run the same CAR regression using the residuals from equation 1 in my main analysis. The results hold the same level of significance as it relates to EARN_SURP * TWEET_VOLUME_QUANT_DAY. This indicates that a greater investor response to a firm's earnings performance occurs when firms use quantitative tweets, which is consistent with the findings around the use of visuals from *Nekrasov et al., 2021*.

VI. Conclusion

In this paper I use tweet activity data directly from Twitter to analyze the volume and content of firm-level earnings-related tweets. I analyze the data using both system programming and hand-collection techniques, providing a unique data-set yet to be analyzed. The findings indicate that firms are less likely to disclose quantitative tweet content if earnings and sales growth are below expectation for the quarter, and that the volume at which this content is tweeted also decreases when earnings are below expectation. I also observe that the firm followers show a higher level of engagement when firms tweet quantitative information and keep that engagement for longer than the tweeting of qualitative information. Additionally, I

find that visuals within tweets are complimentary to the reporting quantitative information, and that those visuals do not garner substantially greater audience attention than non-visual quantitative tweets. Thus, it can be debated whether Twitter followers respond visuals or the content within the visuals.

This paper helps to further the contribution in two main areas of research. First, I expand the social media findings of *Jung et al., 2018*. While our findings differ on the dissemination of EA tweets, I am able to build on the disclosure of earnings-related tweets by analyzing what information earnings-related tweets contain and how often that information is disclosed to followers. Second, I expand the quantitative versus qualitative reporting findings of *Merkley, 2014* & *Miller, 2002*. My findings indicate consistent firm-level behavior, expanding research into the use of social media as a financial disclosure channel.

References

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

Blankespoor, E. (2018). Firm communication and investor response: A framework and discussion integrating social media. *Accounting, Organizations and Society, 68-69*, 80-87.

Blankespoor, E., Miller, G. S., & White, H. D. (2014). The role of dissemination in market liquidity: Evidence from the firms' use of Twitter™. *The Accounting Review, 89*(1), 79-112.

Cade, N. L. (2018). Corporate social media: How two-way disclosure channels influence investors. *Accounting, Organizations and Society, 68-69*, 63-79.

Chou, C., Chang, C. J., Chin, C., & Chiang, W. (2018). Measuring the Consistency of Quantitative and Qualitative Information in Financial Reports: A Design Science Approach. *Journal of Emerging Technologies in Accounting, 15*(2), 93-109.

Crowley, R. M., Huang, W., & Lu, H. (2020). Discretionary Disclosure on Twitter. *Working Paper.*

Dorminey, J. W., Dull, R. B., & Schaupp, L. C. (2015). The effect of SEC approval of social media for information dissemination. *Research in Accounting Regulation, 27*, 165-173.

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

Guindy, M. L., Naughton, J. P., & Riodan, R. (2019). The Chilling Effect of Regulation FD: Evidence from Twitter. *Working paper.*

Huang, X., Nekrasov, A., & Teoh, S. H. (2018). Headline salience, managerial opportunism, and over- and underreactions to earnings. *The Accounting Review, 93*, 231–255.

Huang, X., Teoh, S. H., & Zhang, Y. L. (2014). Tone management. *The Accounting Review, 89*, 1083–1113.

Iankova, S., Davies, I., Archer-Brown, C., Marder, B., & Yau, A. (2019). A comparison of social media marketing between B2B, B2C and mixed business models. *Industrial Marketing Management, 81*, 169-179.

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

Kothari, S. P., Shu, S., & Wysocki, P. D. (2009). Do managers withhold bad news? *Journal of Accounting Research, 47(1)*, 241-276.

Lewis, C., and Young, S. (2019). Fad or future? Automated analysis of financial text and its implications for corporate reporting. *Accounting and Business Research, 49*(5), 587-615.

Liberti, J. M., & Petersen, M. A. (2019). Information: Hard and Soft. *Review of Corporate Finance Studies, 8*(1), 1-41.

Mayew, W., Sharp, N., & Vankatachalam, M. (2013). Using earnings conference calls to identify analysts with superior private information. *Review of Accounting Studies, 18,* 386-413

Merkley, K. J. (2014). Narrative Disclosure and Earnings Performance: Evidence from R&D Disclosures. *The Accounting Review, 89*(2), 725-757.

Miller, G. (2002). Earnings Performance and Discretionary Disclosure. *Journal of Accounting Research, 40,* 173-204.

Miller, G. S., & Skinner, D. J. (2015). The Evolving Disclosure Landscape: How Changes in Technology, the Media, and Capital Markets Are Affecting Disclosure. *Journal of Accounting Research, 53*(2), 221-239.

Nekrasov, A., Teoh, S. H., & Wu, S. (2021). Visuals and Attention to Earnings News on Twitter. *Review of Accounting Studies,* 1-43.

Rogers, J. L., Skinner, D. J., & Zechman, S. L. C. (2016). The role of the media in disseminating insider-trading news. *Review of Accounting Studies, 21*, 711-739.

Roulstone, D. T. (2011). Discussion of Large-Sample Evidence on Firms' Year-over-Year MD&A Modifications. *Journal of Accounting Research, 49*(2), 347-357.

Securities and Exchange Commission (SEC). (2000). *Final rule: Selective disclosure and insider trading, 17 CFR Parts 240, 243, and 249*. Retrieved May 20, 2019, from https://www.sec.gov/rules/final/33-7881.htm.

Securities and Exchange Commission (SEC). (2013a). *Release No. 69279, Report of investigation pursuant to Section 21(a) of the Securities Exchange Act of 1934: Netflix, Inc. and Reed Hastings.* Retrieved May 20, 2019, from https://www.sec.gov/litigation/investreport/34-69279.pdf.

Securities and Exchange Commission (SEC). (2013b). *Press Release 2013-51: Sec says social media OK for company announcements if investors are alerted*. Retrieved May 20, 2019, from https://www.sec.gov/News/PressRelease/Detail/PressRelease/1365171513574#.Uj8ASH-FR8E.

Twitter. (n.d.). About verified accounts. Available at: https://help.twitter.com/en/managing-your-account/about-twitter-verified-accounts.

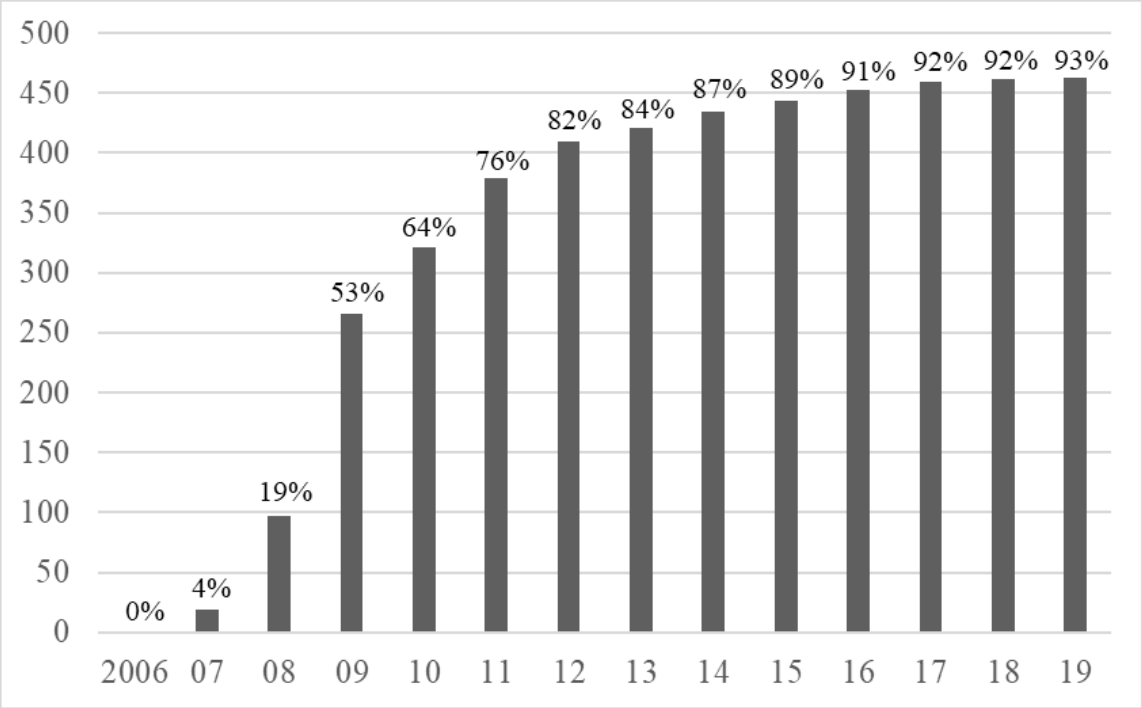
Twitter. (2019). Twitter Announces First Quarter 2019 Results. Available at: https://s22.q4cdn.com/826641620/files/doc_financials/2019/q1/Q1-2019-Earnings-Release.pdf

Walther, J. B., & Jang, J. W. (2012). Communication processes in participatory websites. *Journal of Computer-mediated Communication, 18*(1), 2-15.

Zhou, M., Lei, L., Wand, J., Fan, W., & Wang, A. G. (2015). Social Media Adoption and Corporate Disclosure. *Journal of Information Systems, 29*(2), 23-50.

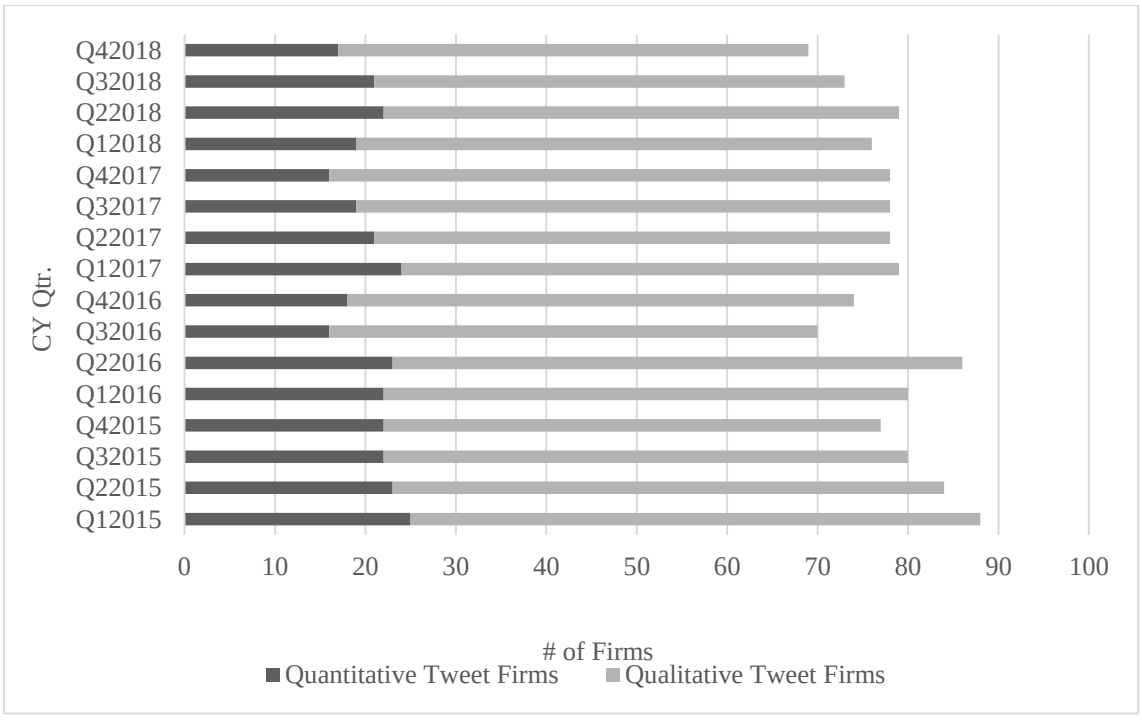
GRAPH 1: Twitter Growth Year-over-Year

This graph shows the growth year-over-year of the firms' Twitter adoption. As 2019, approximately 93% (or 463 firms) maintained a company-owned Twitter account.



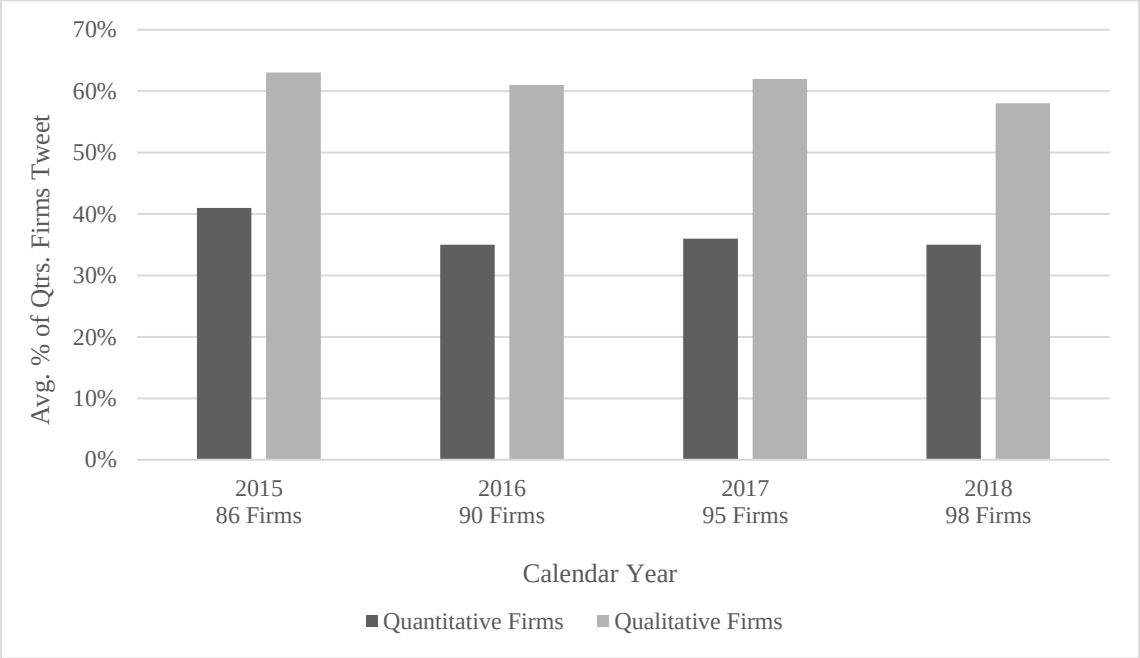
GRAPH 2: Earnings-Related Tweet Firms Qtr-over-Qtr

This graph shows the total number of unique firms that make an earnings-related tweet by quarter. The total is split between the number of quantitative tweeters (firms), followed by the number of qualitative tweeters (firms).



GRAPH 3: Earnings-Related Tweet Firms by Information Content Year-over-Year

This graph shows the percentage of quarters earnings-related tweeting firms tweet either quantitative or qualitative earnings information. The graph is split between the quantitative versus qualitative tweeting activity.



GRAPH 4: Earnings-Related Tweet Firms by Tweeting Consistency Qtr-over-Qtr

This graph shows the percentage of additional firms that tweet quantitative and/or qualitative information content, that did not tweet that content in the prior quarter. The graph is split between the quantitative versus qualitative tweeting activity.

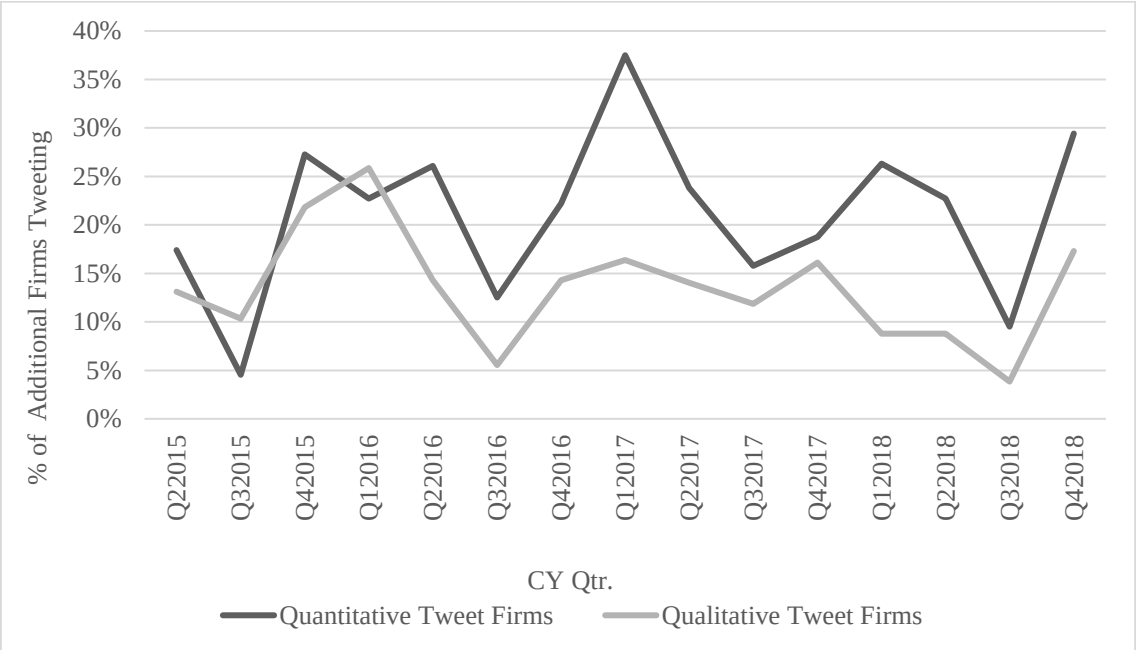


TABLE 1: Sample Description

Panel A: Sample Selection

This table outlines calculations to the final sample size used in the analyses. Incomplete data is due to firms created during the sample period (i.e. spinoffs) and/or insufficient data not available via databases: Compustat, CRSP, IBES & RavenPack.

	# of Tweets	# of Firm Qrts.
Twitter API Tweet Population	279,667	-
Elimination Systematically / Manually	(276,150)	1,305
Elimination due to insufficient data	(643)	(296)
Total Sample	**2,874**	**1,009**

Panel B: Industry Breakout

This table summarizes the industry breakout for the S&P 500 firms, using the Fama-French 10 classification. The first column shows the number of unique firm quarters containing at least one earnings-related tweet. The second column shows the number of quarters in the first column that contain at least one quantitative earnings figure. The third column shows the percentage of firm quarters of the total that contain a quantitative earnings figure.

Industry	# of Earnings Firm Quarters	# of Quantitative Firm Quarters	% of Quantitative Firm Quarters
Consumer Nondurables	67	32	48%
Consumer Durables	12	3	25%
Manufacturing	206	55	27%
Oil, Gas & Coal	83	20	24%
Business Equipment	123	32	26%
Telephone & Television	-	-	-
Wholesale & Retail	125	72	58%
Healthcare, Medical Equipment & Drugs	172	26	15%
Utilities	96	17	18%
Other	125	66	53%
Total:	**1,009**	**323**	**33%**

TABLE 3: EA Tweet Descriptive Statistics – by Quarter

This table shows descriptives for all variables both Twitter variables as well as financial and control variables. For further variable definitions see Appendix A.

Variables	# Firm Qtrs	Mean	St Dev.	Min	P25	Median	P75	Max
QUANT_QTR	*1,009*	0.327	0.469	0	0	0	1	1
QUAL_QTR	*1,009*	0.911	0.285	0	1	1	1	1
TWEET_VOLUME_TOTAL	*1,009*	1.123	0.575	0.693	0.693	0.693	1.386	3.892
TWEET_VOLUME_QUANT	*1,009*	0.339	0.568	0	0	0	0.693	2.708
TWEET_VOLUME_QUAL	*1,009*	0.95	0.543	0	0.693	0.693	1.099	3.555
TOTAL_ENGAGE_RATE	*1,009*	2.682	1.481	0	1.609	2.565	3.497	8.253
AVG_ENGAGE_RATE	*1,009*	1.512	1.063	0	0.693	1.282	2.079	6.56
TWEET_VOLUME_VISUAL	*1,009*	0.104	0.301	0	0	0	0	1.946
MISSFORECAST	*1,009*	0.174	0.38	0	0	0	0	1
SALES_GROWTH	*1,009*	0.042	0.196	-0.512	-0.028	0.04	0.1	0.795
SIZE	*1,009*	9.9	1.097	5.824	8.962	9.923	10.658	12.331
ROA	*1,009*	0.016	0.025	-0.124	0.006	0.015	0.026	0.092
MTB	*1,009*	1.649	1.27	0.112	0.71	1.298	2.067	6.856
MEDIA_NEWS	*1,009*	0.845	0.213	0	0.699	0.845	1	1.462
PRESS_RELEASES	*1,009*	0.358	0.391	0	0	0.301	0.699	1.929
ANALYSTS	*1,009*	2.768	0.43	1.099	2.565	2.833	3.091	3.738
FOLLOWERS	*1,009*	3.827	1.183	0	3.569	3.958	4.438	5.726
FIRM_AGE	*1,009*	47.657	25.217	7	27	49	60	96

TABLE 4: Regression of Earnings Tweet Volume & Information Content to Firm Performance

Volume of:	(1) TWEET_VOLUME_TOTAL (across firms)	(2) TWEET_VOLUME_TOTAL (within firms)	(3) TWEET_VOLUME_QUANT (across firms)	(4) TWEET_VOLUME_QUANT (within firms)	(5) TWEET_VOLUME_QUAL (across firms)	(6) TWEET_VOLUME_QUAL (within firms)
MISSFORECAST	-0.0915***	-0.0419*	-0.0982**	-0.0508**	-0.0515	-0.0155
	(0.0344)	(0.0230)	(0.0400)	(0.0255)	(0.0419)	(0.0318)
SALES_GROWTH	-0.0253	-0.0182	-0.134	-0.0779	0.0815	0.0375
	(0.113)	(0.0775)	(0.102)	(0.0727)	(0.116)	(0.0898)
SIZE	0.155**	0.0238	0.185***	-0.145	0.0754	0.105
	(0.0651)	(0.153)	(0.0639)	(0.110)	(0.0538)	(0.138)
ROA	-0.380	0.831	-1.053	-0.590	0.0727	1.451**
	(1.088)	(0.616)	(1.018)	(0.521)	(0.947)	(0.557)
MTB	0.0379	0.0299	0.0847**	0.0793**	0.0000	-0.0136
	(0.0421)	(0.0486)	(0.0352)	(0.0389)	(0.0429)	(0.0432)
MEDIA_NEWS	0.0831	-0.0226	0.0557	0.00860	0.0509	-0.0583
	(0.221)	(0.0812)	(0.201)	(0.0786)	(0.200)	(0.108)
PRESS_RELEASES	0.162	-0.0265	0.115	-0.0351	0.183	0.0172
	(0.126)	(0.0481)	(0.121)	(0.0477)	(0.117)	(0.0609)
ANALYSTS	0.172	0.0439	0.0577	0.0942	0.214*	-0.0295
	(0.125)	(0.0932)	(0.116)	(0.0820)	(0.111)	(0.0909)
FOLLOWERS	0.0529*	-0.00138	0.0513*	0.0119	0.0298	-0.0129
	(0.0283)	(0.0139)	(0.0266)	(0.0115)	(0.0258)	(0.0132)
FIRM_AGE	-0.00294	-0.00948***	-0.00369**	0.00806***	-0.00189	-0.0171***
	(0.00195)	(0.00314)	(0.00176)	(0.00240)	(0.00194)	(0.00287)
Observations	1,009	1,009	1,009	1,009	1,009	1,009
Adj. R^2 / Pseudo R^2	0.199	0.756	0.261	0.758	0.119	0.633
Quarter FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	NO	YES	NO	YES	NO
Firm FE	NO	YES	NO	YES	NO	YES

The results are from a firm-level probit and OLS regressions, testing the effects of firm characteristics on earnings-related tweet volume and content. The 8 columns show coefficients and z-statistics regressed by a dependent variables as follows: TWEET_VOLUME_TOTAL, a continuous variable indicating the total number of earnings-related tweets made by a firm per quarter, QUANT_QTR, a binary variable equal to 1 if a firm makes a quantitative tweet in a quarter, TWEET_VOLUME_QUANT, a continuous variable indicating the total number of quantitative tweets made by a firm in a quarter, QUAL_QTR the total number of qualitative tweets made by a firm in a quarter, and TWEET_VOLUME_QUAL, a continuous variable indicating the total number of qualitative tweets made by a firm in a quarter. Sample size used is 1,009 unique firm quarters. The independent variables are measured at the firm level and are as follows: MISSFORECAST, indicating if a firm is below expectation for earnings performance, SALES_GROWTH, indicating if a firm had sales growth for the quarter, SIZE, the total assets of a firm, ROA, the total income as a portion of total assets of a firm, MTB, the market to book value of a firm, MEDIA_NEWS, the number of outside news articles written about the firm in the preceding fiscal quarter, PRESS_RELEASES, the number of firm issued press releases of a firm in the preceding fiscal quarter, ANALYSTS, the number of analyst coverage per each firm, FOLLOWERS, the number of Twitter followers of a firm, and FIRM_AGE, the age of the firm. The industry fixed effects are based on Fama-French 10 industry classifications, firm fixed effects are based on firms and the quarterly / year fixed effects are based on financial quarters / years. The results are clustered at the firm-level and all continuous variables are winsorized to the 1^{st} and 99^{th} percentiles.

TABLE 5: Regression of Firm Engagement Rates & Information Content

	(1) TOTAL_ ENGAGE_ RATE	(2) TOTAL_ ENGAGE_ RATE	(3) AVG_ ENGAGE_ RATE	(4) AVG_ ENGAGE_ RATE
TWEET_VOLUME_TOTAL	0.768***		-1.535***	
	(0.100)		(0.144)	
TWEET_VOLUME_QUANT		0.590***		-0.624***
		(0.0925)		(0.116)
TWEET_VOLUME_QUAL		0.476***		-1.280***
		(0.0995)		(0.126)
MISSFORECAST	-0.0795	-0.0743	-0.0578	-0.0450
	(0.0736)	(0.0727)	(0.0692)	(0.0703)
SALES_GROWTH	0.375**	0.389**	0.474**	0.502**
	(0.175)	(0.176)	(0.200)	(0.206)
SIZE	0.494**	0.548***	0.133	0.141
	(0.206)	(0.206)	(0.209)	(0.219)
ROA	0.558	0.855	0.748	0.961
	(1.536)	(1.615)	(1.384)	(1.374)
MTB	0.236***	0.219***	0.0842	0.0705
	(0.0785)	(0.0798)	(0.0702)	(0.0748)
MEDIA_NEWS	-0.128	-0.123	-0.0535	-0.0881
	(0.210)	(0.206)	(0.195)	(0.191)
PRESS_RELEASES	-0.236**	-0.243**	-0.182	-0.141
	(0.0990)	(0.0995)	(0.112)	(0.113)
ANALYSTS	0.189	0.182	0.161	0.115
	(0.206)	(0.203)	(0.187)	(0.189)
FOLLOWERS	0.130**	0.128**	0.115***	0.108***
	(0.0539)	(0.0566)	(0.0392)	(0.0397)
FIRM_AGE	-0.0386***	-0.0425***	-0.0104**	-0.0128**
	(0.00509)	(0.00533)	(0.00521)	(0.00591)
Observations	1,009	1,009	1,009	1,009
Adj R^2	0.760	0.758	0.612	0.609
Quarter FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES

The results are from a firm-level OLS regressions, testing the effects of firm characteristics on earnings-related tweet volume and content. The four columns show coefficients and z-statistics regressed by dependent variables as follows: TOTAL_ENGAGE_RATE, a continuous variable indicating the total engagement rate for all earnings-related tweets by firm per quarter, and AVG_ENGAGE_RATE, a continuous variable indicating the average engagement rate per earnings-related tweet by firm per quarter. Sample size used is 1,009 unique firm quarters. The independent variables are measured at the firm level and are as follows: TWEET_VOLUME_TOTAL, a continuous variable indicating the total number of earnings-related tweets made by a firm per quarter, TWEET_VOLUME_QUANT, a continuous variable indicating the total number of quantitative tweets made by a firm in a quarter, and TWEET_VOLUME_QUAL, a continuous variable indicating the total number of qualitative tweets made by a firm in a quarter, MISSFORECAST, indicating if a firm is below expectation for earnings performance, SALES_GROWTH, indicating if a firm had sales growth for the quarter, SIZE, the total assets of a firm, ROA, the total income as a portion of total assets of a firm, MTB, the market to book value of a firm, MEDIA_NEWS, the number of outside news articles written about the firm in the preceding fiscal quarter, PRESS_RELEASES, the number of firm issued press releases of a firm in the preceding fiscal quarter, ANALYSTS, the number of analyst coverage per each firm, FOLLOWERS, the number of Twitter followers of a firm, and FIRM_AGE, the age of the firm. The industry fixed effects are based on Fama-French 10 industry classifications, firm fixed effects are based on firms and the quarterly / year fixed effects are based on financial quarters / years. The results are clustered at the firm-level and all continuous variables are winsorized to the 1st and 99th percentiles.

TABLE 6: Regression of Earnings Tweet Volume & Tweet Visuals

	(1) TWEET_VOLUME _VISUAL_QUANT (across firms)
MISSFORECAST	-0.0689**
	(0.0300)
SALES_GROWTH	-0.123
	(0.0879)
SIZE	0.135*
	(0.0727)
ROA	-0.891
	(0.861)
MTB	0.0885**
	(0.0372)
MEDIA_NEWS	-0.000174
	(0.183)
PRESS_RELEASES	-0.0516
	(0.104)
ANALYSTS	-0.00376
	(0.0934)
FOLLOWERS	0.0504**
	(0.0229)
FIRM_AGE	-0.00131
	(0.00119)
Observations	1,009
Adj. R^2 / Psuedo R^2	0.155
Quarter FE	YES
Year FE	YES
Industry FE	YES

The results are from a firm-level probit and OLS regressions, testing the effects of firm characteristics on earnings-related tweet volume and content. The 2 columns show coefficients and z-statistics regressed by a dependent variable as follows: TWEET_VOLUME_VISUALS, a continuous variable indicating the total number of earnings-related tweets made by a firm per quarter that contain a quantitative figure within an image. Sample size used is 1,009 unique firm quarters. The independent variables are measured at the firm level and are as follows: MISSFORECAST, indicating if a firm is below expectation for earnings performance, SALES_GROWTH, indicating if a firm had sales growth for the quarter, SIZE, the total assets of a firm, ROA, the total income as a portion of total assets of a firm, MTB, the market to book value of a firm, MEDIA_NEWS, the number of outside news articles written about the firm in the preceding fiscal quarter, PRESS_RELEASES, the number of firm issued press releases of a firm in the preceding fiscal quarter, ANALYSTS, the number of analyst coverage per each firm, FOLLOWERS, the number of Twitter followers of a firm, and FIRM_AGE, the age of the firm. The industry fixed effects are based on Fama-French 10 industry classifications, firm fixed effects are based on firms and the quarterly / year fixed effects are based on financial quarters / years. The results are clustered at the firm-level and all continuous variables are winsorized to the 1st and 99th percentiles.

TABLE 7: Regression of Firm Engagement Rates & Tweet Visuals

	(1) TOTAL_ ENGAGE_ RATE	(2) AVG_ ENGAGE_ RATE
TOTAL_VOLUME_VISUAL_QUANT	0.464***	-0.480***
	(0.137)	(0.0971)
TWEET_VOLUME_NON_VISUAL_QUANT	0.473***	-0.574***
	(0.109)	(0.127)
TWEET_VOLUME_QUAL	0.451***	-1.261***
	(0.104)	(0.126)
MISSFORECAST	-0.0782	-0.0437
	(0.0725)	(0.0707)
SALES_GROWTH	0.385**	0.505**
	(0.179)	(0.206)
SIZE	0.541***	0.145
	(0.205)	(0.212)
ROA	0.788	1.022
	(1.615)	(1.379)
MTB	0.215***	0.0753
	(0.0816)	(0.0750)
MEDIA_NEWS	-0.132	-0.0761
	(0.206)	(0.196)
PRESS_RELEASES	-0.241**	-0.146
	(0.101)	(0.112)
ANALYSTS	0.190	0.109
	(0.204)	(0.189)
FOLLOWERS	0.131**	0.105**
	(0.0566)	(0.0403)
FIRM_AGE	-0.0420***	-0.0130**
	(0.00534)	(0.00583)
Observations	1,009	1,009
Adj R^2	0.759	0.608
Quarter FE	YES	YES
Year FE	YES	YES
Firm FE	YES	YES

The results are from a firm-level OLS regressions, testing the effects of firm characteristics on earnings-related tweet volume and content. The two columns show coefficients and z-statistics regressed by dependent variables as follows: TOTAL_ENGAGE_RATE, a continuous variable indicating the total engagement rate for all earnings-related tweets by firm per quarter, and AVG_ENGAGE_RATE, a continuous variable indicating the average engagement rate per earnings-related tweet by firm per quarter. Sample size used is 1,009 unique firm quarters. The independent variables are measured at the firm level and are as follows: TWEET_VOLUME_VISUAL_QUANT, a continuous variable indicating the total number of earnings-related tweets made by a firm per quarter with images that contain quantitative figures, TWEET_VOLUME_NO_VISUAL_QUANT, a continuous variable indicating the total number of tweets made by a firm in a quarter that do not have images but have quantitative figures, and TWEET_VOLUME_QUAL, a continuous variable indicating the total number of qualitative tweets made by a firm in a quarter, MISSFORECAST, indicating if a firm is below expectation for earnings performance, SALES_GROWTH, indicating if a firm had sales growth for the quarter, SIZE, the total assets of a firm, ROA, the total income as a portion of total assets of a firm, MTB, the market to book value of a firm, MEDIA_NEWS, the number of outside news articles written about the firm in the preceding fiscal quarter, PRESS_RELEASES, the number of firm issued press releases of a firm in the preceding fiscal quarter, ANALYSTS, the number of analyst coverage per each firm, FOLLOWERS, the number of Twitter followers of a firm, and FIRM_AGE, the age of the firm. The industry fixed effects are based on Fama-French 10 industry classifications, firm fixed effects are based on firms and the quarterly / year fixed effects are based on financial quarters / years. The results are clustered at the firm-level and all continuous variables are winsorized to the 1st and 99th percentiles.

TABLE 8: Regression of Market Return & Quantitative Tweeting

	(1) CAR (1-day pre/post) QUANT_DAY	(2) CAR (1-day pre/post) TWEET_VOLUME_ QUANT_DAY
EARN_SURP * QUANT_DAY	0.000997**	0.00106**
	(0.000462)	(0.000408)
EARN_SURP * SALES_SURP	-0.000054	-0.000052
	(0.000071)	(0.000072)
EARN_SURP * SIZE	-0.000344	-0.000356
	(0.000285)	(0.000286)
EARN_SURP * ROA	0.0274***	0.0272***
	(0.00880)	(0.00882)
EARN_SURP * MTB	-0.000450*	-0.000456*
	(0.000242)	(0.000241)
EARN_SURP * MEDIA_NEWS	0.000485	0.000453
	(0.00122)	(0.00125)
EARN_SURP * PRESS_RELEASES	-0.000006	0.000006
	(0.000551)	(0.000551)
EARN_SURP * ANALYSTS	-0.000202	-0.000256
	(0.000561)	(0.000573)
EARN_SURP * FOLLOWERS	-0.000025	-0.000044
	(0.000197)	(0.000199)
EARN_SURP * FIRM_AGE	0.0000019	0.000002
	(0.000009)	(0.000009)
EARN_SURP	0.00363	0.00396
	(0.00237)	(0.00240)
QUANT_DAY	-0.00472*	-0.00669***
	(0.00272)	(0.00252)
SALES_SURP	0.000529	0.000532
	(0.000579)	(0.000578)
SIZE	-0.0106	-0.0106
	(0.00719)	(0.00715)
ROA	-0.0892*	-0.0888*
	(0.0455)	(0.0455)
MTB	-0.00268	-0.00257
	(0.00267)	(0.00264)
MEDIA_NEWS	-0.00223	-0.00223
	(0.00928)	(0.00940)
PRESS_RELEASES	-0.00529	-0.00534
	(0.00404)	(0.00400)
ANALYSTS	0.00172	0.00219
	(0.00681)	(0.00685)
FOLLOWERS	0.000834	0.000944
	(0.00139)	(0.00140)
FIRM_AGE	0.000098	0.000107
	(0.000192)	(0.000191)
Observations	3,771	3,771
Adj R^2	0.058	0.058
Quarter FE	YES	YES
Year FE	YES	YES
Firm FE	YES	YES

The results are from a firm-level OLS regressions, testing the effects of tweet content on cumulative market returns. The one column shows coefficients and z-statistics regressed by the dependent variable CAR, a continuous variable calculating the cumulative market return one day prior to through one day post a firm's tweet day. Sample size used is 3,771 firm days. The independent variables are as follows: EARN_SURP, a decile ranked variable from 0 to 10 indicating the level of earnings surprise of a firm and QUANT_DAY, a binary variable with the value of 1 if a firm made a quantitative tweet within that firm day, and 0 otherwise. The control variables remain consistent with the other analyses. The industry fixed effects are based on Fama-French 10 industry classifications, firm fixed effects are based on firms and the quarterly / year fixed effects are based on financial quarters / years. The results are clustered at the firm-level and all continuous variables are winsorized to the 1st and 99th percentiles.

Appendix A: Definition of Variables

Firm Variables:

Variable	Definition
MISSFORECAST	Binary variable set to 1 if the firm's quarterly actual EPS is less than the forecasted EPS
EARN_SURP	Decile ranked variable taking the value between 0 to 10, measuring the level of earnings surprise from actual to forecasted EPS
SALES_GROWTH	Percentage change in sales of current quarter from the prior-year quarter
SALES_SURP	Decile ranked variable taking the value between 0 to 10, measuring the level of sales growth surprise of actual current quarter from the prior-year quarter
SIZE	Natural logarithm of the firm's quarterly total assets
ROA	Firm's quarterly income before extraordinary items divided by the firm's total assets
MTB	Firm's quarterly market value of equity divided by the firm's book value of equity
MEDIA_NEWS	Log of 1 plus the quarterly number of "earnings" related news articles of the firm
PRESS_RELEASES	Log of 1 plus the number of firm's quarterly "earnings" related press-releases
ANALYSTS	Natural logarithm of the quarterly number of financial analysts following a firm
FOLLOWERS	Log of 1 plus the number of Twitter followers of a firm's account
FIRM_AGE	The difference between the calendar quarter year and the firm's IPO year

Twitter Variables:

Variable	Definition
TWEET_VOLUME_TOTAL	Log of 1 plus the number of firm earnings-related tweets made during the quarter
QUANT_QTR	Binary variable set to 1 if the firm tweeted a quantitative earnings-related tweet during the quarter
QUANT_DAY	Binary variable set to 1 if the firm tweeted a quantitative earnings-related tweet on a day basis
TOTAL_VOLUME_QUANT	Log of 1 plus the number of firm quantitative earnings-related tweets made during the quarter
QUAL_QTR	Binary variable set to 1 if the firm tweeted a qualitative earnings-related tweet during the quarter
TWEET_VOLUME_QUAL	Log of 1 plus the number of firm qualitative earnings-related tweets made during the quarter
VISUAL_QUANT_QTR	Binary variable set to 1 if the firm tweeted a visual with qualitative information in an earnings-related tweet during the quarter
TWEET_VOLUME_VISUALS_QUANT	Log of 1 plus the number of firm quantitative tweets with an image made during the quarter
TWEET_VOLUME_NON_VISUALS_QUANT	Log of 1 plus the number of firm quantitative tweets without an image made during the quarter
TOTAL_ENGAGE_RATE	Log of 1 plus the firm's total number of retweets and favorites to earnings-related tweets made during the quarter
AVG_ENGAGE_RATE	*TOTAL_ENGAGE_RATE* divided by the number of earnings-related tweets made by a firm during the quarter

Appendix B: Earnings-related keyword listing

Below is a complete list of financial keywords used.

Q1	1qtr	financial	equity
q1	1 qtr	Sale	Value
1Q	2Qtr	sale	value
1q	2 Qtr	Sales	EBITDA
Q2	2qtr	sales	ebitda
q2	2 qtr	Revenue	EBIT
2Q	3Qtr	revenue	ebit
2q	3 Qtr	Revenues	Gross income
Q3	3qtr	revenues	gross income
q3	3 qtr	Profit	Gross margin
3Q	4Qtr	profit	gross margin
3q	4 Qtr	Profits	Gross sales
Q4	4qtr	profits	gross sales
q4	4 qtr	Loss	Income
4Q	Qtr	loss	income
4q	qtr	Losses	Income from operations
Quarter 1	Fiscal year	losses	income from operations
quarter 1	fiscal year	Gain	Net income
Quarter One	FY	gain	net income
quarter one	fy	Gains	Operating
Quarter 2	Annual	gains	operating
quarter 2	annual	Return	Profit margin
Quarter Two	Semi-Annual	return	profit margin
quarter two	semi-annual	Returns	GAAP
Quarter 3	Semi Annual	returns	gaap
quarter 3	semi annual	Dividends	Non-GAAP
Quarter Three	Press release	dividends	non-GAAP
quarter three	press release	Growth	non-gaap
Quarter 4	Earnings release	growth	Non GAAP
quarter 4	earnings release	Forecast	non GAAP
Quarter Four	annual report	forecast	non GAAP
quarter four	Annual Report	Expense	Adjusted
Qtr1	audit	expense	adjusted
Qtr 1	Audit	Expenses	EPS
qtr1	10-K	expenses	eps
qtr 1	10K	Cost	Earnings per share
Qtr2	10k	cost	earnings per share
Qtr 2	10-Q	Costs	Free cash flow
qtr2	10Q	costs	free cash flow
qtr 2	10q	Cash	Pro forma
Qtr3	Disclosure	cash	pro forma
Qtr 3	disclosure	Cash flow	Pro-forma
qtr3	SEC	cash flow	pro-forma
qtr 3	Accounting	Results	Core earnings
Qtr4	accounting	results	core earnings
Qtr 4	Financial statement	Earning	Funds for operations
qtr4	financial statement	earning	funds for operations
qtr 4	Financial statements	Earnings	
1Qtr	financial statements	earnings	
1 Qtr	Financial	Equity	

Appendix C: Example of Tweet Classification

Quantitative Tweet (QUANT_QTR, TWEET_VOLUME_QUANT):



Qualitative Tweet (QUAL_QTR, TWEET_VOLUME_QUAL):

