Pump it Up?

Tweeting to Manage Investor Attention to Earnings News

Vineet Bhagwat[*]   Timothy R. Burch[†]

December 2016[‡]

Abstract

We examine how firms' tweeting behavior affects earnings-news returns. Tweeting about earnings news increases the magnitude of announcement returns, particularly when the earning surprise is small and positive and when the firm is less visible as measured by firm size or analyst coverage. We also find evidence of strategic tweeting, particularly by firms that manage earnings: financial tweeting is more frequent around positive earnings surprises, especially those that are less visible. Overall, we conclude Twitter provides firms an effective and strategic way to mitigate investors' limited attention to news, especially when the news is otherwise less likely to attract notice.

JEL classification: G14
Keywords: Social media; Twitter; Investor limited attention; Earnings news

[*]Lundquist College of Business, University of Oregon.

[†]University of Miami School of Business.

[‡]Correspondence to Vineet Bhagwat, Lundquist School of Business, Finance Department, Lillis 382, 1208 University of Oregon, Eugene, OR 97403, or Timothy Burch, University of Miami School of Business, 514-Jenkins, P.O. Box 248094, Coral Gables, FL 33124-6552, tburch@miami.edu, 305-284-1509 (o), 305-284-4800 (f).

Pump it Up?

Tweeting to Manage Investor Attention to Earnings News

Abstract

We examine how firms' tweeting behavior affects earnings-news returns. Tweeting about earnings news increases the magnitude of announcement returns, particularly when the earning surprise is small and positive and when the firm is less visible as measured by firm size or analyst coverage. We also find evidence of strategic tweeting, particularly by firms that manage earnings: financial tweeting is more frequent around positive earnings surprises, especially those that are less visible. Overall, we conclude Twitter provides firms an effective and strategic way to mitigate investors' limited attention to news, especially when the news is otherwise less likely to attract notice.

"...we came across the word 'twitter,' and it was just perfect. The definition was 'a short burst of inconsequential information,' and 'chirps from birds'...bird chirps sound meaningless to us, but meaning is applied by other birds. The same is true of Twitter: a lot of messages can be seen as completely useless and meaningless, but it's entirely dependent on the recipient."

Jack Dorsey, cofounder of the social media and microblogging service Twitter, on the origin of the service's name (from an interview published in *The Los Angeles Times* on February 18, 2009).

1.   Introduction

Quarterly earnings news has an enormous cumulative impact on the firm's value and stock price. Despite the importance of earnings news, however, traditionally the literature finds underreaction to individual earnings releases (Bernard and Thomas (1989,1990)) and papers such as Dellavigna and Pollet (2009) and Hirshleifer, Lim, and Teoh (2009) present evidence that underreaction to earnings news may be explained by investors' limited attention. Although some authors report post-earnings announcement drift (and thus underreaction) is less pronounced in more recent samples (Ayers, Li, and Yeung (2011), there remains considerable variation in the stock-return reaction to earnings announcements that is not explained solely by the earnings news itself.

This paper investigates how the corporate use of Twitter, which provides firms a direct way to push stock-related information in real time to potential investors, alters investor attention and thus how stock prices react to corporate news. Specifically, we provide evidence

on how a firm's tweeting activity affects stock price reactions to earnings news.[1] We expect a firm's Twitter use to affect stock price reactions to earnings news for two potential reasons. First, a firm's tweets do not have to overcome third-party editorial decisions about newsworthiness, and thus tweets provide an additional source of information promulgated only by the firm itself.[2] Second, Twitter and other social media outlets allow firms to push financial news to potential investors who may not otherwise seek out or observe financial news. For example, a social media user who follows a firm's tweets for product market news may not be tuned into traditional financial news outlets that cover the firm, but will nonetheless receive the financial news that the firm tweets. Thus, Twitter gives firms the ability to reach a pool of potential investors that may become interested in the firm's stock upon seeing financial news. Both of these channels should work to increase investor attention to earnings news.[3]

Figure 1 provides context for the types of questions we pursue. The relative frequency of tweets with financial content shows a strong seasonal pattern that correlates with earnings announcements. Do firms adopt a fixed tweeting policy with respect to financial news around earnings releases, or do they attempt to strategically influence their stock price by increasing attention to earnings news when doing so will have a more pronounced and positive impact? If firms are strategic, is this behavior effective? Prior research shows that firms manage their earnings to meet or beat analyst forecasts (see Healy and Wahlen (1999) for a review), presumably due in part to stock-price-based incentives. Managing earnings through discretionary accruals, however, is less prevalent since the passage of the Sarbanes-Oxley Act

---

[1]To be clear, we examine tweets made by the firm itself, not by other Twitter users about the firm.

[2]Evidence in Blankespoor, Miller, and White (2014), Chen, De, Hu, and Hwang (2014), and Chen, Hwang, and Liu (2013) collectively demonstrate using stock market data that Twitter is a complement to other sources of stock-relevent information flow (e.g., the financial press), not merely a substitute. We contrast our paper with these in a later section.

[3]Our focus on Twitter is largely based on data availability, but it is likely that other forms of social media affect the reaction to corporate news through similar channels.

(SOX) in 2002 (Cohen, Dey, and Lys (2008)). It is possible that social media provides a way to manage investor reaction to earnings, as opposed to managing earnings themselves.

We identify 918 firms with Twitter accounts as of 2013 and obtain their entire tweet history from account inception (over 3.4 million tweets). Although firms tweet about a variety of topics, our focus is on the extent to which firms issue tweets that specifically refer to impending or just announced earnings, or financial information related to the earnings release. To the extent that investors are constrained in their attention, these financial tweets should affect investor attention to earnings news and could thus impact trading behavior.

The notion that a firm's tweets should influence investor attention leads us to develop and investigate two hypotheses. The first is that the absolute magnitude of earnings announcement returns, controlling for the magnitude of the earnings news itself, will be increasing in the frequency of financial tweets during the days preceding the earnings announcement. That is, greater financial tweeting prior to the earnings release will cause the stock price reaction to positive earnings news to be more positive, and the negative stock price reaction to negative earnings news to be more negative. This hypothesis should hold more strongly if tweeting policy is exogenous, i.e., if firms employ a fixed tweeting policy that is not conditional on the earnings results they are reporting.

The second is that the marginal impact of financial tweets on announcement returns will be greater for earnings announcements that are less likely to be noticed, either because the earnings news is relatively less visible or salient, or because investors already have a high level of attention. Twitter provides an additional channel of earnings news dissemination, and should have less impact for earnings news that is already likely to be noticed.

To investigate whether financial tweeting has a stronger impact for less visible earnings announcements, we use two visibility measures based on the earnings news itself, and two visibility measures based on firm characteristics. The first earnings-specific measure is the

3

sign of the earnings surprise (as measured based on analysts' expectations). Consistent with the efforts many firms make to avoid it, falling short of earnings expectations, even by a small amount, is much more likely to attract attention (e.g., coverage in the financial press) than beating expectations by a similar amount. The second earnings-specific measure is the *magnitude* of the earnings surprise. All else equal, larger-magnitude earnings surprises should be more salient than smaller-magnitude earnings surprises.

The two *firm-level* visibility measures we use are firm size and the number of analysts following the firm, respectively. Larger firms will attract more coverage of their earnings news by traditional media, for example, and similarly, firms with more analyst coverage will have their earnings results covered and disseminated more broadly by the professional analyst industry. Finally, we also exploit pre-earnings-announcement searches for the firm or its ticker on Google to identify periods of time during which investors are already actively seeking out information about the firm or its stock. When this is the case, the second hypothesis predicts financial tweeting will have a smaller impact on announcement returns because investor attention is already heightened.

To test the predictions hypothesized above, we measure the percent of the firm's tweets that are explicitly related to an imminent or just-released earnings announcement, which we label financial tweets.[4] Using cross-sectional regressions that control for firm fixed effects, the time period, and a wide variety of firm-specific controls, we first document weak evidence that, conditional on the earnings news, the absolute magnitude of the announcement return is increasing in the percent of financial tweets during the announcement period. This evidence is consistent with the first hypothesis in which larger-magnitude earnings announcement returns are expected for higher levels of pre-announcement financial tweeting.

---

[4]Later we discuss the tradeoff between using the percent versus the number, but results are robust to either measure. We also discuss robustness to various ways of classifying a tweet as financial.

We also note that the evidence does not support a reverse causality channel in which expected or realized earnings announcement returns drive the firm's tweeting activity. Under such a reverse causality channel, the more negative the announcement return (or expected announcement return) is, the less intense should be the firm's financial tweeting activity. This predicts a positive correlation between financial tweeting intensity and announcement returns, but for negative earnings surprises we find that financial tweeting intensity and announcement returns are uncorrelated.

Results supporting the second hypothesis regarding earnings visibility are stronger both statistically and economically. We find that for positive (but not negative) earnings surprises, a greater proportion of financial tweets during the few days surrounding the earnings release is associated with higher announcement returns. Moreover, we find that earnings tweets have their greatest impact when analyst expectations are surpassed by less than two cents. These results are consistent with financial tweets having a larger impact on investor behavior for earnings results that are less salient on their own. As an example of the economic impact, for small, positive earnings surprises a one standard deviation increase in financial tweeting during the period beginning one trading day before the earnings announcement date end ending just prior to the earnings announcement increases the predicted announcement return from 0.671% to 1.156%. We further find that the impact on announcement returns is not subsequently reversed.

Next, we exploit the firm-level visibility measures. Conditional on the earnings surprise, financial tweets by less visible firms (whether measured by firm size or analyst following) are associated with significantly higher announcement returns, but only when earnings surprises are small and positive. Tweeting by more visible firms has no significant impact. We also find that for the subset of firms in which we are able to examine Google search data, the effect of financial tweeting on announcement returns is much stronger when pre-announcement Google search intensity is low.

The contrasting evidence for positive versus negative earnings news further motivates our investigation of whether firms tweet strategically. If firms are aware that financial tweeting around positive earnings news positively affects returns, but doing so for negative news does not, they may have incentives to tailor their tweeting activity accordingly. Consistent with firms using Twitter as a platform to manage investor response to earnings announcements, we find that financial tweeting intensity during the three-day window surrounding earnings news is higher for positive earnings news than for negative news.

This finding raises the question of whether reverse causality may explain the correlation we find between announcement returns and financial tweeting, given that returns are higher for positive earnings news. Even though the strategic tweeting result is seemingly consistent with a reverse causality explanation for the correlation between announcement returns and tweeting, it is important to point out why the overall results do not support reverse causality. *Inconsistent* with reverse causality, we do not find correlation between returns and tweeting within the sample of large, positive earnings news (when earnings results exceed analyst expectation by two or more cents). Moreover, we do not find any correlation between returns and tweeting when earnings news is negative. In a reverse causality channel, contemporaneous tweeting should be a function of observed returns more generally, instead of only in a subsample of small, positive earnings news.

For completeness, we also investigate tweeting during the post-announcement period. Firms may wish to continue to draw greater attention to positive earnings results, particularly those less likely to be noticed. Consistent with this, we find evidence of strategic tweeting during the *post-announcement* period. Specifically, firms issue more financial tweets during the post announcement period following positive earnings surprises, but only when the surprise is small and thus less likely to garner attention through traditional channels. Moreover, we find it is the firms that more often engage in earnings management that issue more financial tweets following such earnings news. Thus, firms with a history of managing

6

earnings to influence their stock prices also tweet more heavily about small, positive earnings results that are less likely (due to their smaller magnitude) to garner as much attention through more traditional channels.

Overall, our results imply that a firm's strategic use of Twitter impacts the way in which stock prices respond to earnings news. This finding has broader implications in that a wide variety of social media could be used strategically to manage the way stock market investors respond to corporate news more generally. In light of the SEC's April 2013 reiteration that using social media complies with the disclosure requirements of Regulation Fair Disclosure ("Reg FD"), corporate use of social media to communicate with and influence the behavior of investors is likely to grow.[5] Our findings suggest the SEC should monitor closely the evolution of corporate social media use and its impact on stock prices.

2. Twitter Background, Prior Literature, and Hypothesis Development

Twitter was created in 2006, and the year 2009 marked a major increase in its use. According to a June 2009 report by the business intelligence firm Sysomos, 72.5% of Twitter users at that time had opened their accounts during the first five months of 2009, and Twitter experienced "hockey stick-like growth" during these months in terms of new account creation (Cheng, Evans, and Singh (2009)). Figure 2 plots the cumulative number of firms with Twitter accounts in our sample, and in Figure 3 we plot the monthly number of tweets by firms in our sample. These figures show impressive growth over time in corporate Twitter use.

---

[5]It is possible that in the future firms will more heavily rely on social media to disclose material news. For example, in early October 2015, Goldman Sachs announced that for its third quarter earnings on October 15 it would not release results on Business Wire as it had done in the past, but instead release them on its own web site and issue a tweet to alert investors to the release.

Although Twitter is most well known as a site for social interaction between individual users, as Figures 2 and 3 illustrate, its use by firms has become very popular. Indeed, Twitter actively promotes itself for business purposes.[6] Although there are also other social media sites used for business purposes (e.g., many firms have Facebook pages), we choose to study Twitter due to the ability to obtain a searchable, time-series database of date-stamped content from which to measure the intensity and specific content of its use.[7] In addition, the content of firms' tweets shows that firms change their tweeting behavior around earnings results. As shown in Figure 1, there is a strong seasonal pattern within the calender year in the percent of tweets that are financial (defined later), and these financial tweets correlate strongly with earnings seasons. Although we discuss robustness of our results to alternative methods of defining tweets that are earnings-related, the strong seasonality validates the method we use in our main results.

Several recent papers document various ways in which social media affects financial markets. Blankespoor, Miller, and White (2014) find that firms' tweets of links to press releases result in increased stock liquidity, and Chen, Hwang, and Liu (2016) find that tweeting by CEOs and CFOs provides incremental information that both predicts returns and increases liquidity. Chen, De, Hu, and Hwang (2014) find that the tone of posted comments that follow user-generated investment opinions on Seekingalpha.com predicts stock returns.[8]

---

[6]Many corporate Twitter users have retail products and have obvious marketing reasons to use social media. For example, "@McDonalds Twitter Team" had eight employees listed on McDonald's web site as of September 2015. However, there are also firms without a large retail consumer market that actively tweet, such as Alcoa.

[7] Jung et. al. (2014) find that "given the choice between the two social media platforms, firms have a stronger preference for Twitter—of the firms that disseminate earnings news via social media, 91% use Twitter and 52% use Facebook."

[8]Heimer (2014) finds that the propensity to be an active rather than passive investor positively correlates with proxies for being more social. Thus, it is possible that this return predictability is explained by investors who interact through social media tending to be active traders and thus more likely to respond to trading cues from others.

None of these papers study the effect of firms' use of social media on stock price return reaction to corporate news events.

Chawla, Da, Xu, and Ye (2014) track retweets of news by Twitter users as a measure of information diffusion, and find that the fraction of retweeting during the first 10 minutes following news correlates with faster price adjustments and stronger trading intensity. Our paper differs from those above in its focus on the interaction between the firm's tweeting activity and price reactions to news, as well as its investigation of potentially strategic tweeting based on the direction and magnitude of news. In concurrent work, Jung, Naughton, Tahoun, and Wang (2016) analyze the choice of firms to use various social media platforms to promote earnings news. Their focus is primarily on voluntary disclosure choices, and they find that the choice of a consistent social media disclosure policy as opposed to sporadic social media use affects trading patterns around earnings news.[9]

The hypotheses we test are straightforward and based on three premises. First, we rely on the premise that investors have limited attention, as argued in many papers such as Dellavigna and Pollet (2009), Hirshleifer, Lim, and Teoh (2009), Huang, Nekrasov, and Teoh (2013), Klibanoff, Lamont, and Wizman (1998), and Louis and Sun (2010). Second, we rely on the assumption that firms with Twitter accounts have a reasonable number of followers, so that financial tweets are seen by potential investors. For justification, we note that a 2011 snapshot of firms in our sample shows the mean number of Twitter followers for each firm at the time was 114,436 (the median is 33,455, and the 25th percentile is 10,451).[10]

---

[9]The sample of firms using Twitter in their study (708) is smaller than ours (918), which is perhaps explained by their limiting their sample to S&P 1500 firms. See also Zhou, Lei, Wang, Fan, and Wang (2014) for a study of firm decisions regarding the use of Twitter versus Facebook for corporate disclosure.

[10]Given the large number of Twitter followers most firms have, it is likely a high percentage of these potential investors are retail investors. Thus, our focus on stock returns also implicitly assumes that retail trading affects prices (as evidenced in papers such as Barber and Odean (2008),

Finally, we assume that a new information channel to focus attention should have its greatest impact for news that is less likely to be noticed. Large earnings surprises, for example, are more salient and thus already attract greater trading volume and result in larger-magnitude announcement returns than do smaller earnings surprises.[11]

These premises lead to two straightforward hypotheses that we test:

H1: Controlling for other factors (including the earnings surprise), the magnitude of earnings announcement returns will be increasing in the intensity of financial tweeting activity.

H2: Controlling for other factors (including the earnings surprise), the impact of financial tweeting activity on earnings announcement returns will be larger for earnings results that are less likely to be noticed.

To test *H1*, we use the absolute value of the announcement cumulative abnormal return (CAR) as described in the next section. To test H2, we use four measures of salience and also a measure of Google searches on the internet for information about the firm or its stock. The first two are based on the earnings results themselves: the magnitude of the earnings surprise (where smaller surprises are less salient) and the sign of the earnings surprise (where positive surprises are less salient). As reviewed in Healy and Wahlen (1999), a large literature documents that many firms use accounting flexibility to minimize the number of

---

Barber, Odean, and Zhu (2009), Burch, Emery, and Fuerst (2014), Hvidkjaer (2008),and Kumar and Lee (2006)).

[11]For example, in our sample the mean abnormal trading volume (the trading volume during the announcement window divided by the trading volume during trading days -45 to -15) is 2.13 for earnings that beat expectations by two cents or more, versus 1.78 for earnings that beat expectations by less than 2 cents. Of course, one could alternatively hypothesize that larger-magnitude earnings surprises, since they are traditionally found to have larger underreaction, would be more impacted by financial tweets. Ultimately, whether it is the reaction to smaller- or larger-magnitude financial tweets that are most strongly impacted by financial tweets is an empirical question on which our study provides evidence.

times reported earnings fall short of expectations. Thus, we contend negative earnings are naturally more salient than positive earnings of similar magnitude. The next two visibility measures are at the firm level, based on the assumption that earnings results by less visible firms receive less coverage by the press and professional analysts. Accordingly, we use firm size (the market value of equity) and the number of analysts following the firm as third and fourth visibility measures. Our measure of internet searches is derived from Google Trends, which provides an index of search volume in google (we provide more detail when we discuss results).

3. Data

We begin with active publicly-traded firms in the Center for Research in Security Prices (CRSP) database at the end of 2013 (we exclude closed-end funds, real-estate investment trusts, limited partnerships, and American depository receipts). So we can control for certain firm characteristics, we obtain from Compustat the book value of assets, cash, research and development (R&D) expense, the book value of debt, property, plant, and equipment (PPE), and inventory for the fiscal year of Twitter account creation through 2013. From the Thomson-Reuters Institutional Holdings 13(f) Database, we also record the number of shares held by 13(f) filers. Firm years missing any of these variables are eliminated.[12] In addition, we retain only firm years in which these firm characteristics are the latest available prior to at least one quarterly earnings per share announcement in the I/B/E/S database.

We restrict the sample to only those firms that have a Twitter account by April 2014. To construct data on each firm's Twitter presence, we search for Twitter accounts by hand via the search feature on Twitter's web site. Before including a Twitter account, we inspect the

_____

[12]An exception is R&D. As is common, we plug missing R&D as a zero due to Compustat's propensity to assign a missing value to most firms that report very low values on their books.

content of some of its tweets, and also visit the firms' web site listed on its Twitter account page (if a site is listed there), to eliminate false matches. For example, our identification method would exclude a Twitter account containing the name McDonalds that turns out to be that of a local dry-cleaning store.[13]

To obtain the entire tweet history of a firm's Twitter account, we use the Twitter application programming interface (https://dev.twitter.com) and also the search feature on Twitter's web site. For firms that have multiple accounts, because our goal is to define a measure that captures the firm's overall tweeting activity, we sum all tweets during the day across the firm's accounts.[14] Using this daily count of tweets, for each firm's quarterly earnings announcement we tabulate the number of tweets (and those that are financial as defined below) over three trading-day windows around the announcement date: [-22,-2], [-1, Announcement], and [+2,+22], where Announcement refers to one second before the time stamp of the earnings news announcement.

We identify financial tweets as those containing the word "earning" or "conference call" (irrespective of capitalization and whether singular or plural, although we do take care to not count tweets that include words such as "learning", "yearning", etc.), or containing a "cashtag" of the firm's ticker symbol, implying the firm has designated the tweet as relevant for investors. For example, a tweet that Apple wishes to flag as relevant for its stock investors will include the cashtag "$AAPL" (in which "$" is contiguously followed by the stock ticker to construct the cashtag). Casual inspection of tweets shows that many firms follow this convention, and thus we classify tweets containing a dollar sign followed by the firm's ticker

---

[13]We also do not include Twitter accounts that have less than one tweet every ten days. This results in excluding eight firms from our final sample.

[14]Seventy-eight percent of firms in our sample have only one account, and only eight percent have more than two.

symbol as financial tweets.[15] We recognize there could be tweets we classify as financial that are not related to earnings, but casual inspection reveals this is unlikely, due to our main focus on financial tweets during the few days surrounding the earnings announcement. And to the extent this sort of miscoding adds noise, the seasonality shown in Figure 1 using our definition nonetheless strongly suggests that our measure correlates with earnings seasons throughout the year. We note that our results are robust to alternative coding schemes, however.[16]

Using our classifications of tweet content, we calculate the percent of tweets that are financial over various trading-day windows around each firm's earnings announcement date. The advantage of using the percent of financial tweets instead of the number is that it distinguishes between, say, four financial tweets out of 10 total, and four financial tweets that are cluttered by 50 non-financial tweets during the same time period that are thus less likely to stand out relative to the four tweets in former example. Nonetheless, our results are robust to using the number of financial tweets instead.

Quarterly earnings announcement dates are from the I/B/E/S database, and for each firm we include earnings announcements made after the firm's Twitter account is established.

[15]To illustrate, below are three sequential financial tweets (dates, times, and content) by Alcoa (19:43 in the first tweet maps to 7:43 pm).

10/7/2013 19:43: $AA Reminder, Alcoa to Host Webcast of Third Quarter 2013 Results Tomorrow, Tuesday, 10/8, beginning at 5pm ET. http://t.co/uUWaQCFFdv

10/8/2013 20:05 $AA Reports #Alcoa3Q13: 3Q profit driven by strong operating performance http://t.co/8Kzy2K70Wd

10/8/2013 20:05 $AA Reports #Alcoa3Q13: Solid revenue of $5.8 billion http://t.co/pdk1lpjUnO

[16]Specifically, results are robust to defining financial tweets by three different methods, all of which exclude the stock ticker hashtag. The first is to limit financial tweets to those that include either "earning" or "conference call" (or their plural). The second is the same as the first but also adds "revenue" and "quarterly" as qualifying words. The third additionally adds "CEO" and "CFO" as qualifying words.

For each EPS announcement, from CRSP we obtain returns over a given window relative to the earnings announcement date. Specifically, we calculate cumulative abnormal returns (CARs) as the sum of daily abnormal returns, where an abnormal return is the firm's return minus the size- and B/M-matched quintile portfolio return (obtained from Kenneth French's website), winsorized at the top and bottom 1%. The final sample contains 918 firms with Twitter accounts and 8,836 EPS observations for these firms covering EPS announcements from the first quarter after Twitter account creation through 2013.

Next, we calculate a standardized unexpected earnings (SUE) measure for each firm's quarterly earnings announcement. Following papers such as Kasznik and Lev (1995) and Loh and Warachka (2012), we define SUE as the actual earnings result minus the mean analyst earnings forecast prior to the announcement, divided by the firm's stock price seven trading days prior to the announcement. For each announcement we calculate the announcement CAR over trading days [-1,+1], winsorized at the top and bottom 1% level (later we also examine a post-announcement window, which is similarly winsorized).

Table 1 presents the summary statistics for our sample. We do not attempt to ascertain statistical differences between above- and below-median tweeters for the characteristics we report.[17] Rather, we report these statistics to describe the data and motivate the need to control for firm characteristics in the analysis that follows. The mean value of book assets for all firms in our sample is $9.7 billion. However, those firms that are above-median tweeters (based on their number of tweets during 2012-2013) are significantly larger than those that are below-median tweeters (mean book assets of $11.5 billion as opposed to $6.9 billion). In addition, above-median tweeters have a slightly higher market-to-book ratio (2.25 versus 1.91) but appear less likely to engage in R&D activity (51% versus 64%). Above-median and below-median tweeting firms have similar levels of cash/assets, market

_____

[17]We classify firms into above- and below-median tweeter groups based on the total number of tweets during the 2012-2013 period.

leverage, institutional holdings, and property, plant and equipment relative to their assets. Above-median tweeting firms appear more likely to pay dividends, and tweet about five times during the announcement window [-1, Announcement] versus less than one tweet on average for below-median tweeting firms. It is below-median tweeters, however, that have a higher percent of their tweets that are financial and thus directly targeted to investors.

4.   Empirical Results

4.1.   Evidence on Hypotheses 1 and 2

To begin, in Table 2 we report the results of cross-sectional ordinary least squares regressions that either explain the absolute value of the announcement CAR (models 1-2) or the raw announcement CAR (models 3-6) for every firm-quarter earnings announcement. All models include firm fixed effects, as well as fixed effects for each year-quarter, so that no results are driven by fixed omitted firm-level factors or a potential time trend in post-earnings announcement returns. In addition, unless otherwise noted we control for the absolute value of SUE, the log of book assets, the market-to-book and cash-to-asset ratios, indicators for whether the firm engages in research and development and pays dividends, the ratio of property, plant, and equipment to assets, market leverage, and institutional ownership. T-statistics are calculated from heteroskedasticity-robust standard errors, clustered at the firm level.

The results in Models (1) and (2) indicate that, conditional on the earnings news, the magnitude of announcement returns is increasing in the percent of tweets that are financial. Model (1) only includes the absolute value of SUE and fixed effects, whereas Model (2) includes the full array of controls. The result is only significant at the 10% level, however, and the economic magnitude is such that a one-standard deviation (SD) increase in *% Financial Tweets* during [-1, Announcement] is associated with the predicted value of the absolute

announcement CAR increasing from 6.16% to 6.32% in model (1) and 6.30% to 6.47% in model (2). Thus, these regression results provide somewhat weak evidence consistent with *H1*.

Support for *H2* in Table 2 is stronger. In models (3)-(8) we divide the sample into positive and negative earnings surprises, and use an indicator variable to isolate the marginal impact of financial tweets when earnings results are smaller in magnitude. Specifically, we define *Small positive surprise* as an indicator set to 1 for earnings that beat the mean analyst estimate by less than two cents. Of the 6,347 observations in the positive earnings surprise subsample, 32% have Small positive surprise coded as 1. Similarly, we define Small negative surprise as an indicator set to 1 for firm earnings announcements that miss the mean analyst earnings forecast by less than two cents. Of 2,489 observations in the negative earnings surprise subsample, 30% have Small negative surprise coded as 1.

In Model (3) of Table 2 for positive earnings news, the coefficient on *% Financial tweets* is positive and weakly significant, which is again consistent with *H1*. In Model (4) we add *Small positive surprise,* an indicator set to one if the earnings exceeds the average analyst forecast by less then two cents, as well as its interaction with *% Financial tweets.* For *H2*, the variable of interest is the interaction term, the coefficient on which is positive and significant ($t = 2.87$). The estimated parameters imply a large economic impact: for small, positive surprises, a one-SD increase in the percentage of financial tweets is associated with an increase in the announcement CAR from 0.67% to 1.17%. The impact for large surprises is not statistically significant, and even if it were, the estimated parameters only imply an analogous increase in the CAR from 3.23% to 3.33%. Thus, financial tweeting has a much less pronounced effect on stock returns for earnings results that are more visible on their own.

In model (5) we remove *SUE* from the set of control variables, since there may be a concern in model (4) about the extent to which *Small positive surprise* and *SUE* are highly correlated. The main result of interest, which is the coefficient and statistical significance on the interaction between *Small positive surprise* and *% Financial tweets,* remains qualitatively unchanged.

Models (6)-(8) do not show significant results for negative surprises, which are more salient earnings results. Thus, models (3)-(8) collectively show, consistent with *H2,* that it is for the least salient earnings news (small-magnitude, positive earnings surprises) that greater financial tweeting intensity during the announcement window is associated with higher-magnitude announcement returns.

It is worth noting these results seem difficult to reconcile with a reverse causality channel in which announcement returns determine the firm's announcement-window tweeting. Under this channel, one would expect that for negative earnings surprises the magnitude of the associated announcement returns would influence financial tweeting frequency. For example, if the market response to a negative earnings result was particularly negative, firms would be even less eager to call attention to such earnings. If anything, they may wish to tweet with *non-financial* information (product market information, for example) in order to quickly distract investors or at least change the narrative to something more positive, thus reducing the value of *% Financial tweets*. This would predict that for negative earnings, *financial* tweeting and announcement returns would be positively correlated (i.e., more negative returns would be associate with fewer financial tweets as we have defined them). Instead, the correlation not statistically significant. Thus, despite evidence we present further below on strategic tweeting, reverse causality does not seem to explain the correlation between *% Financial tweets* and the absolute value of announcement returns shown in Models (1) and (2).

To further corroborate the notion that tweeting matters more for news that is otherwise less likely to attract attention, in Table 3 we limit the sample to positive earnings surprises (results for negative surprises are insignificant), and estimate regressions on subsamples grouped by firm visibility measures. *H2* predicts that financial tweeting will have a greater impact for low visibility firms, and the models confirm this expectation. Models (1) and (2) split the sample based on above- and below-market capitalization (measured at the latest data prior to 30 days before the earnings announcement). Lower market capitalization firms (the Model (1) sample) have lower visibility, for example, in that they attract less media coverage (Fang and Peress (2009)).

In Models (3) and (4) we split the sample based on the number of analysts that issued earnings forecast for the earnings observation, where below-median analyst coverage implies lower visibility. The interaction between *Small positive surprise* and *% Financial tweets* is positive and significant in Models (1) and (3) (the low visibility samples) but insignificant in Models (2) and (4) (the high visibility samples). Although the main focus in Blankespoor, Miller, and White (2014) and Chen, Hwang, and Liu (2016) is different than ours, they too find a more significant impact of tweeting for less visible firms.

In Table 4, we repeat the analysis from Table 2 but split the earnings sample into those in which Google searches during the pre-announcement window were above- or below-median. To define these two sample groups, for each firm-earnings observation we use Google Trends to obtain the index of search volume Google provide during the period starting 22 days prior and ending one day prior to the earnings announcement date, and calculate the mean search

index across all observations in the 22 to -1 period.[18] Then, for each firm, we take the median across all earnings observations in our sample.

Under H2, we expect the results observed in Table 2 will be stronger in panel A (which is the below-median sample) than in panel B. Comparing columns (1)-(5) in Panel A (the relevant results from Table 2) to those in Panel B, indeed this is the case.[19]

In the first two models of Table 5, we investigate whether the result for small, positive surprises is permanent or whether it is reversed in the post-announcement window, by estimating regressions that explain post-announcement CARs (which are measured over days +2 to +22, although results are similar using +2 to +45 or +2 to +60). Table 2 shows that *announcement* returns are larger for small, positive earnings surprises accompanied by more frequent financial tweets, so a reversal would imply that *post-announcement* returns would be *smaller*. We do not find, however, that any of the announcement-window tweeting variables in models (1) and (2) are significant in explaining post-announcement returns. Thus, the effects documented in Table 2 are not later reversed during the post-announcement window. Models (3)-(4) of this table investigate the potential effect of *contemporaneous* financial tweeting during the post-announcement window. Such tweeting does not appear to impact post-announcement returns.

---

[18]The google search index data for our firms is provided with calendar-week freqency. For a given earnings announcement, we include any google data week that ends on or after the 22nd trading day prior to the earnings announcement date, provided that the google week ends no later than one trading day before the earnings announcement date. In this way we assure that no google search data is contaminated with searches that took place on the announcement date or later.

[19]Economic significance in Panel A is similar to that in Table 2. For example, in model (1) a one-SD increase in % Financial Tweets is associated with the predicted value of the absolute announcement CAR increasing from 6.10% to 6.29%, and in model (1) the comparable effect is an increase from 6.12% to 6.34%. In model (4) the impact for small, positive surprises is that a one-SD increase in % Financial Tweets is assiciated with an increase in CAR from 0.71% to 1.54%.

In summary, the results thus far weakly support *H1* and more strongly support *H2*. Overall, the announcement return results are consistent with financial tweeting drawing investor attention to positive earnings announcements that are otherwise less attention-grabbing. Financial tweeting is positively correlated with announcement returns only for small positive surprises (as compared to large positive surprises), and for firms that are less likely to naturally garner attention due to their smaller size or lower level of analyst coverage. Finally, the impact of contemporaneous financial tweeting during the announcement window is not reversed during the post-announcement period.

4.2. Do firms tweet strategically?

In this section we investigate the possibility that firms are strategic in their tweeting. Whereas the preceding analysis takes the firm's tweeting activity as given and analyzes how stock returns correlate, in this section we analyze the extent to which firms alter their tweeting activity based on the type of earnings news released. Specifically, we investigate how *% Financial tweets* correlates with both the sign and magnitude of earnings surprises.

It seems natural that firms would want to draw greater attention to positive earnings results compared to negative results. In addition, motivated by our earlier finding that tweeting is more impactful for news less likely to be noticed, we speculate that firms may be aware of this and more intensively engage in financial tweeting for smaller magnitude versus larger magnitude positive earnings news. We do not have any expectations for the *timing* of such strategic tweeting, however. For example, although firms with positive earnings news may be tempted to engage in financial tweeting during the pre-announcement window, they could also fear SEC scrutiny if they differentially tweet before positive versus negative earnings releases.

In Table 6 we report regressions that explain *% Financial tweets* during various windows on the basis of the direction and magnitude of earnings results. There is no evidence of greater tweeting intensity during the pre-announcement window based on the direction or magnitude of earnings news (Models (1), (4), and (7)). However, financial tweeting intensity during the *announcement* window is stronger for positive earnings news in Model (2), as the predicted value of % Financial tweets increases from 4.15% to 5.42% when *Positive surprise* equals one. And within the sample of positive earnings surprises, Model (6) implies that the predicted value of *% Financial tweets* during the *post-announcement* window [+2, +22] increases from 0.77% to 1.12% when the positive earnings news is small in magnitude. Thus, it seems firms change their financial tweeting strategy based on both the direction and magnitude of their earnings news. It is possible that firms are not satisfied with the announcement reaction to small, positive earnings results, and thus attempt to increase investor attention to the results in the few weeks that follow. Models (7)-(9) show that firms do not increase tweeting around negative earnings results, which also makes strategic sense.

In untabulated results, we estimate the regressions in Table 6 but remove *SUE* as a control variable to remove any concerns about the indicator variables we use being highly correlated with SUE. The results are qualitatively similar.

In Table 7, we examine whether the evidence of strategic tweeting is stronger for firms that seem to engage more heavily in earnings management. As long as investors are not able to detect earnings management at the time of the earnings release, tweeting strategically provides firms yet another tool with which to influence their stock price around earnings releases. We view firms that have managed their earnings as having demonstrated a preference for such types of strategic behavior.

To measure the firm's recent level of earnings management, we use the absolute value of abnormal discretionary accruals during the prior year from the modified Jones (1991) model

described in Dechow, Sloan, and Sweeney (1995).[20] We repeat the first six regressions of Table 6 and include the absolute value of accruals, *Abs(Accruals)*, as well as its interaction with either *Positive surprise* (Models (1)-(3)) or *Small positive surprise* (Models (4)-(6)). Model (2), which repeats the specification in Model (2) of Table 6, shows that firms increase financial tweeting intensity during the announcement window for positive earnings news irrespective of their propensity to engage in earnings management, as the interaction between *Positive surprise* and *Abs(Accruals)* is insignificant. Model (6), however, which repeats the specification in Model (6) of Table 6, shows that financial tweeting intensity after small positive earnings news is greater for firms that more heavily manage their earnings through accruals. This suggests that firms that are more likely to strategically manage their earnings results are also more likely to strategically tweet following these results.

4.3. Robustness to how financial tweets are measured

In Table 8 we repeat regression models (3) and (4) of Table 2 for the sample of positive earnings surprises, using alternative methods of defining financial tweets. The first alternative method defines a financial tweet as one that includes either "earning" or "conference call" (or their plural), which is similar to the definition we use in our main analysis but excluding the cashtag of the firm's stock symbol. The second alternative method is similar, but also adds "revenue" and "quarterly" as qualifying words. The third method additionally adds "CEO" and "CFO" as qualifying words. The key results for any of these alternative definitions of financial tweets are qualitatively similar. Models (1), (3), and (5) show that announcement returns are positively correlated with announcement-window financial tweeting (for the sample of positive earnings surprises on which the regressions are estimated), and models (2), (4), and (6) show this effect is particularly strong when positive earnings

---

[20]The results are robust to using alternate accrual models that control for performance (Kothari et al. (2005)) or the quality of accruals (Dechow and Dichev (2002)).

surprises are small. In untabulated results we have also confirmed our other key results (e.g., based on firm visibility or those that explain the propensity to issue financial tweets) are robust to these alternative ways of defining financial tweets.

4.4. Conclusion

The way firms communicate with investors has changed dramatically due to the internet. Not only can firms post information on web sites investors may visit when they look for news about the firm, but thanks to social media sites such as Twitter, firms can build a captive audience to which they can actively push information to computer screens, tablets, and mobile devices to capture investor attention.

Exploiting the frequency, timing, and content of firms' tweets on the social media site Twitter, this paper investigates whether such direct firm-to-public information flow affects earnings-related stock returns. We find that, conditional on the earnings news, when firms more frequently tweet financial information around the announcement of earnings results, announcement returns are larger in magnitude. This result is particularly strong when earnings results are less visible or salient, and the effect on returns is not reversed in the post-announcement window. Moreover, we find that firms tweet strategically by increasing the frequency of financial tweets during and after the release of positive earnings results, suggesting they are aware of the impact such tweeting can have. Firms that more often engage in earnings management are also more likely to tweet strategically. Overall, we find that corporate use of Twitter impacts stock returns for positive earnings news that is less likely to be noticed, and at least some firms seem to take advantage.

References

[1] Ayers, Benjamin C., Oliver Zhen Li, and P. Eric Yeung, 2011, Investor Trading and the Post-Earnings-Announcemetn Drift, *The Accounting Review* 82, 385-416.

[2] Barber, Brad M., and Terrance Odean, 2008, All That Glitters: The Effect of Attention and News on the Buying Behavior of Individual and Institutional Investors, *The Review of Financial Studies* 21, 785-818.

[3] Barber, Brad M., Terrance Odean, and Ning Zhu, 2009, Do Retail Trades Move Markets? *The Review of Financial Studies* 22, 151-186.

[4] Bernard, Victor, and Jacob Thomas, 1989, Post-Earnings-Announcement Drift: Delayed Price Response or Risk Premium? *Journal of Accounting Research* (Supplement), 1-36.

[5] Bernard, Victor, and Jacob Thomas, 1990, Evidence that Stock Prices do Not Fully Reflect the Implications of Current Earnings for Future Earnings, *Journal of Accounting and Economics* 13, 305-340.

[6] Blankespoor, Elizabeth, Gregory Miller, and Hal White, 2014, The Role of Dissemination in Market Liquidity: Evidence From Firms' Use of Twitter, *The Accounting Review* 89, 79-112.

[7] Burch, Timothy, Douglas Emery, and Michael Fuerst, 2014, Who Moves Markets in a Sudden Market-Wide Crisis? Evidence from Nine-Eleven, *Journal of Financial and Quantitative Analysis* 51, 463-487.

[8] Chawla, Nitesh, Zhi Da, Jian Xu, and Mao Ye, 2014, Catching Fire: An Anatomy of Information Diffusion using Retweets, University of Notre Dame working paper.

[9] Chen, Hailang, Prabuddha De, Yu Hu, and Byoung-Hyoun Hwang, 2014, Wisdom of Crowds: The Value of Stock Opinions Transmitted through Social Media, *The Review of Financial Studies* 27, 1367-1403.

[10] Chen, Hailang, Byoung-Hyoun Hwang, and Baixiao Liu, 2016, Economic Consequences of Social Media Adoption by CEOs and CFOs, Cornell University working paper.

[11] Cheng, Alex, Mark Evans, and Harshdeep Singh, 2009, Inside Twitter: An In-Depth Look Inside the Twitter World, www.sysomos.com.

[12] Cohen, Daniel A., Aiyesha Dey, and Thomas Z. Lys, 2008, Real and Accrual-Based Earnings Management in the Pre- and Post-Sarbarnes-Oxley Periods, *The Accounting Review* 83, 757-787.

[13] Dechow, Patricia and Ilia Dichev, 2002, The Quality of Accruals and Earnings: The Role of Accrual Estimation Errors, *The Accounting Review* 77, 35-59.

[14] Dechow, Patricia M., Richard G. Sloan, and Amy P. Sweeney, 1995, Detecting Earnings Management, *The Accounting Review* 70, 193-225.

[15] DellaVigna, Stefano and Joshua Pollet, 2009, Investor Attention and Friday Earnings Announcements, *The Journal of Finance* 64, 709-749.

[16] Fang, Lily, and Joel Peress, 2009, Media Coverage and the Cross-section of Stock Returns, *The Journal of Finance* 64, 2023-2052.

[17] Healy, Paul, and James Wahlen, 1999, A Review of the Earnings Management Literature and Its Implications for Standard Setting, *Accounting Horizons* 13, 365-383.

[18] Heimer, Rawley, 2014, Friends Do Let Friends Buy Stocks Actively, *Journal of Economic Behavior and Organization* 107, 527-540.

[19] Hirshleifer, David, Sonya Seongyeon Lim, and Siew Hong Teoh, 2009, Driven to Distraction: Extraneous Events and Underreaction to Earnings News, *The Journal of Finance* 64, 2289-2325.

[20] Huang, Xuan, Alex Nekrasov, and Siew Hong Teoh, 2013, Headline Salience and Over- and Underreactions to Earnings, Working paper, University of California, Irvine.

[21] Hvidkjaer, Soeren, 2008, Small Trades and the Cross-Section of Stock Returns? *Review of Financial Studies* 21, 1124-1151.

[22] Jones, Jennifer J., 1991, Earnings Management during Import Relief Investigations, *Journal of Accounting Research* 29, 193-228.

[23] Jung, Michael, James Naughton, Ahmed Tahoun, and Clare Wang, 2016, Do Firms Strategically Dissemimate? Evidence from Corporate Use of Social Media, working paper, New York University.

[24] Klibanoff, Peter, Owen Lamont, and Thierry Wizman, 1998, Investor Reaction to Salient News in Closed-End Country Funds, *The Journal of Finance* 53, 673-699.

[25] Kasznik, Ron and Baruch Lev, 1995. To Warn or Not to Warn: Management Disclosures in the Face of an Earnings Surprise, *The Accounting Review* 70, 113-134.

[26] Kothari, S.P., Andrew Leone, and Charles Wasley, 2005, Performance Matched Discretionary Accrual Measures, *Journal of Accounting and Economics* 39, 163-197.

[27] Kumar, Alok., and Charles M. C. Lee, 2006, Retail Investor Sentiment and Return Comovements, *Journal of Finance* 61, 2451-2486.

[28] Loh, Roger and Mitch Warachka, 2012, Streaks in Earnings Surprises and the Cross-Section of Stock Returns, *Management Science* 58, 1305-1321.

[29] Louis, Henock and Amy Sun, 2010, Investor Inattention and the Market Reaction to Merger Announcements, *Management Science* 56, 1781-1793.

[30] Zhou, Mi (Jamie), Lijun (Gillian) Lei, Jianling Wang, Weiguo (Patrick) Fan, and Alan G. Wang, 2014, Social Media Adoption and Corporate Disclosure, *Journal of Information Systems* 29, 23-50.

Table 1
Summary Statistics
This table reports summary statistics for the sample of firm-quarter earnings announcements from one quarter after Twitter account creation to 2013Q4. "Below Median" and "Above Median Tweeting Firms" are determined using all tweeting activity (financial or otherwise) by firms in our sample from 2012-2013. CARs are the sum of daily firm returns minus returns of a size/B-M ratio quintile matched portfolio, and are winsorized at the 1% level on both tails. *SUE* is a standardized unexpected earnings measure, calculated by subtracting the mean analyst forecast from the actual earnings, and then dividing by the firm's stock price seven trading days prior to the earnings release. *Small positive surprise* is an indicator set to 1 for firm earnings that beat the mean analyst estimate by less than two cents. *Small negative surprise* is analogous, based on earnings that miss the mean analyst earnings forecast by less than two cents. *M/B* is the firm's market value of assets divided by the book value of assets. *Firm engages in R&D* is an indicator set to 1 if reported research and development expense is positive, and 0 if otherwise or missing. *Firm pays dividends* is an indicator set to 1 if the firm paid a dividend in the last fiscal year, and 0 otherwise, *% Held by institutions* is the percentage of the firm's shares held by institutions that file Form 13f as reported in Thomson Reuters. *M/B*, *Cash/Assets*, *PP&E/Assets*, *Market leverage*, and *% Held by institutions* are all winsorized at the 1% level. *Number of tweets* is the total number of any type of tweet during the relevant window and *% Financial tweets* is the percent of tweets during the measurement window that are classified as "financial". Tweets are classified as "financial" if they contain a "cashtag" (a dollar sign) followed by the firm's stock ticker (i.e. "$AAPL" for Apple's tweets) or the words "earning" or "conference call" (irrespective of singular or plural, but excluding occurrences in parts of words like "learning" or "yearning, etc.).

	All Firm/Quarters		Below Median Tweeting Firms		Above Median Tweeting Firms	
	N=8,836		N=3,439		N=5,397	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Announcement CAR [-1,+1]	0.40	8.69	0.23	8.69	0.58	8.62
SUE	0.01	2.55	0.02	2.39	0.01	2.47
Small positive surprise	0.21	0.41	0.20	0.40	0.23	0.42
Small negative surprise	0.09	0.29	0.10	0.30	0.08	0.28
Book Assets	9,665	27,431	6,876	27,389	11,543	27,545
M/B	2.10	1.44	1.91	1.25	2.25	1.55
Cash/Assets	0.22	0.21	0.23	0.23	0.22	0.19
Firm engages in R&D	0.56	0.50	0.64	0.48	0.51	0.50
Firm pays dividends	0.40	0.49	0.36	0.48	0.43	0.50
PP&E/Assets	0.32	0.24	0.32	0.23	0.33	0.25
Market leverage	0.14	0.16	0.15	0.17	0.13	0.15
% Held by institutions	0.66	0.27	0.63	0.28	0.69	0.25
Number of tweets [-22,-2]	16.31	46.30	2.93	9.29	24.83	59.82
Number of tweets [-1,Ann]	3.11	9.11	0.71	2.70	5.08	11.61
Number of tweets [+2,+22]	25.71	70.90	4.61	15.79	39.16	91.19
% Financial tweets [-22,-2]	2.06	11.04	5.25	17.90	0.50	4.20
% Financial tweets [-1,Ann]	4.91	16.88	10.02	24.55	2.80	11.66
% Financial tweets [+2,+22]	0.97	7.57	2.13	11.94	0.39	3.62

Table 2
Announcement CARs and Financial Tweeting

This table reports OLS regressions in which the dependent variable is the absolute announcement CAR in columns 1-2 and the announcement CAR in columns 3-6. All announcement CARs are measured over days [-1,+1] and winsorized at the 1% level on both tails. *% Financial tweets* is the percent of tweets during the measurement window that are classified as financial. *Small positive surprise* is an indicator variable set to 1 for earnings that beat the mean analyst forecast by less than two cents. *Small negative surprise* is analogous, based on earnings that miss the mean analyst earnings forecast by less than two cents. Models (3)-(4) restrict the sample to positive earnings surprises (earnings that beat the mean forecast), and Models (5)-(6) restrict the sample to negative earnings surprises (earnings that fall below the mean forecast). All columns include quarterly and firm fixed effects, and t-statistics from firm-clustered standard errors are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable:	Abs. Value Announcement CAR [-1,+1]		Announcement CAR [-1,+1]					
Surprise Type:	All Announcements		Positive Surprise			Negative Surprise		
% Financial Tweets [-1,Announcement]	0.015*	0.016*	0.019*	0.015	0.011	0.011	0.010	0.012
	(1.78)	(1.76)	(1.79)	(0.07)	(0.66)	(0.30)	(0.44)	(0.37)
Small positive surprise * (% Financial Tweets)				0.07***	0.06***			
				(2.91)	(2.80)			
Small negative surprise * (% Financial Tweets)							-0.01	0.01
							(-0.21)	(0.34)
Small positive surprise				-2.94***	-3.13***			
				(-8.17)	(-8.92)			
Small negative surprise							2.31***	2.55***
							(3.04)	(3.58)
Absolute Value of SUE	0.30***	0.22***	1.59***	1.24***		-0.04	-0.07	
	(4.01)	(3.21)	(3.92)	(3.24)		(-0.23)	(-0.42)	
Ln(Assets)		0.31	-2.98***	-3.03***	-2.99***	-3.62**	-3.41*	-3.23*
		(0.54)	(-2.74)	(-2.81)	(-2.86)	(-2.00)	(-1.84)	(-1.77)
M/B		0.20	-1.24***	-1.25***	-1.21***	-1.65**	-1.56**	-1.47**
		(1.45)	(-4.11)	(-4.31)	(-4.15)	(-2.34)	(-2.25)	(-2.02)
Cash/Assets		-3.59**	-1.31	-1.11	-1.81	-5.55	-7.06	-7.41
		(-2.53)	(-0.44)	(-0.37)	(-0.62)	(-0.79)	(-1.02)	(-1.04)
Firm engages in R&D		-1.55*	5.01	4.08	4.17	-0.07	-0.51	-1.05
		(-1.79)	(0.80)	(0.63)	(0.69)	(-0.02)	(-0.17)	(-0.30)
Firm pays Dividends		-0.23	-0.02	0.16	-0.07	0.06	0.18	1.11
		(-0.55)	(-0.03)	(0.21)	(-0.08)	(0.04)	(0.13)	(0.69)
PP&E/Assets		1.40	4.27	3.67	2.39	-16.94*	-18.06*	-18.97*
		(0.56)	(0.81)	(0.72)	(0.43)	(-1.72)	(-1.81)	(-1.87)
Market leverage		4.45**	8.15**	7.30*	10.39***	6.37	6.41	9.43
		(2.07)	(2.12)	(1.91)	(2.59)	(0.78)	(0.79)	(1.12)
% Held by institutions		0.00	0.92	0.80	0.52	1.38	1.00	1.14
		(0.01)	(0.76)	(0.68)	(0.43)	(0.77)	(0.56)	(0.63)
Constant	6.20***	10.99	36.48***	38.38***	40.29***	47.26***	46.68***	36.11**
	(49.07)	(1.02)	(4.35)	(4.62)	(4.92)	(3.15)	(3.07)	(2.40)
Observations	8,836	8,836	6,347	6,347	6,347	2,489	2,489	2,489
R-squared	0.03	0.31	0.25	0.27	0.26	0.38	0.39	0.39

Firm-clustered robust t-statistics in parentheses.

All columns include quarterly and firm fixed effects.

*** p<0.01, ** p<0.05, * p<0.1

Table 3
Effect of Tweeting on Announcement CARs for High versus Low Visibility Firms

This table reports OLS regressions in which the dependent variable is the announcement CAR over days [-1,+1], winsorized at the 1% level on both tails. The sample is restricted to positive surprises (earnings that beat the mean forecast) for all models. *% Financial tweets* is the percent of tweets during the measurement window that are classified as financial. *Small positive surprise* is an indicator variable set to 1 for earnings that beat the mean analyst forecast by less than two cents. Models (1)-(2) divide the sample into below- and above-median market value of equity while Models (3)-(4) divide the sample into below- and above-median analyst coverage. All columns include quarterly and firm fixed effects, and t-statistics from firm-clustered standard errors are in parentheses.

	(1)	(2)	(3)	(4)
Dependent Variable:	Announcement CAR [-1,+1]			
Firm Characteristic:	Market Equity		Analyst Coverage	
Size of Characteristic:	Small	Large	Small	Large
% Financial Tweets during [-1,Announcement]	-0.025	0.014	0.008	-0.004
	(-0.68)	(1.29)	(0.28)	(-0.19)
Small positive surprise * (% Financial Tweets)	0.14***	0.02	0.09***	0.01
	(2.70)	(0.69)	(2.64)	(0.98)
Small positive surprise	-3.79***	-2.19***	-3.61***	-2.40***
	(-6.46)	(-6.04)	(-6.48)	(-6.40)
SUE	1.24***	1.45**	1.21***	1.59***
	(4.04)	(2.17)	(3.32)	(2.86)
Ln(Mkt. Equity)	-1.10	-1.85		
	(-0.66)	(-1.02)		
Ln(Analyst Coverage)			1.04	0.21
			(1.19)	(0.17)
Ln(Assets)	-3.13	-1.57	-5.90***	-1.67
	(-1.28)	(-0.74)	(-3.73)	(-1.25)
M/B	-0.78	-1.58**	-1.32***	-1.10***
	(-0.94)	(-2.19)	(-2.61)	(-2.75)
Cash/Assets	1.50	-5.97*	-2.33	-3.29
	(0.34)	(-1.95)	(-0.61)	(-0.90)
Firm engages in R&D	10.75***	2.95	10.06***	3.96
	(7.35)	(0.72)	(6.57)	(0.99)
Firm pays Dividends	0.87	-0.23	1.04	-0.49
	(0.61)	(-0.25)	(0.80)	(-0.52)
PP&E/Assets	8.93	-5.43	4.01	-1.66
	(0.93)	(-0.91)	(0.50)	(-0.25)
Market leverage	4.84	-4.42	10.12*	3.79
	(0.62)	(-0.62)	(1.87)	(0.74)
% Held by institutions	2.43	0.11	3.37*	0.04
	(1.12)	(0.10)	(1.85)	(0.03)
Constant	33.31***	53.25***	40.76***	33.90***
	(2.99)	(5.07)	(3.74)	(2.97)
Observations	3,173	3,174	3,173	3,174
R-squared	0.34	0.23	0.34	0.26

Firm-clustered robust t-statistics in parentheses.

All columns include quarterly and firm fixed effects.

*** p<0.01, ** p<0.05, * p<0.1

Table 4
Effect of Tweeting on Announcement CARs by Above- versus Below-median Google Search Volume

This table reports OLS regressions in which the dependent variable is the absolute announcement CAR in columns 1-2 and the announcement CAR in columns 3-6. All definitions and specifications are identical to Table 2. Panel A restricts the sample to the earnings announcement where Google search volume for the firm was below-median, while Panel B restricts the observations to those announcements with above-median Google search volume.

Panel A: Below-median Google search volume

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable:	Abs. Value Announcement CAR [-1,+1]		Announcement CAR [-1,+1]					
Surprise Type:	All Announcements		Positive Surprise			Negative Surprise		
% Financial Tweets [-1,Announcement]	0.02*	0.02*	0.02*	0.02	0.01	0.01	0.02	0.01
	(1.84)	(1.88)	(1.81)	(0.07)	(0.69)	(0.38)	(0.55)	(0.41)
Small positive surprise * (% Financial Tweets)				0.15***	0.11***			
				(2.87)	(2.91)			
Small negative surprise * (% Financial Tweets)							-0.01	0.01
							(-0.21)	(0.34)
Small positive surprise				-3.11***	-3.13***			
				(-6.12)	(-8.92)			
Small negative surprise							2.54***	2.76***
							(3.00)	(3.42)
Absolute Value of SUE	0.42***	0.32***	1.66***	1.71***		-0.05	-0.11	
	(3.87)	(3.21)	(3.92)	(3.24)		(-0.23)	(-0.42)	
All Controls	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,045	5,045	3,243	3,243	3,243	1,314	1,314	1,314
R-squared	0.05	0.33	0.28	0.31	0.31	0.39	0.41	0.41

Firm-clustered robust t-statistics in parentheses. All columns include quarterly and firm fixed effects.
*** p<0.01, ** p<0.05, * p<0.1

Panel B: Above-median Google search volume

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable:	Abs. Value Announcement CAR [-1,+1]		Announcement CAR [-1,+1]					
Surprise Type:	All Announcements		Positive Surprise			Negative Surprise		
% Financial Tweets [-1,Announcement]	0.01	0.02	0.01	0.01	-0.01	-0.11	0.02	0.01
	(1.02)	(0.89)	(1.11)	(0.34)	(-0.21)	(-0.42)	(0.37)	(0.38)
Small positive surprise * (% Financial Tweets)				0.08	-0.02			
				(0.51)	(-0.23)			
Small negative surprise * (% Financial Tweets)							0.02	0.04
							(0.35)	(0.11)
Small positive surprise				0.56	0.21			
				(0.89)	(0.30)			
Small negative surprise							0.04	0.89
							(0.76)	(0.45)
Absolute Value of SUE	0.46***	0.29***	1.57***	1.80***		-0.05	-0.11	
	(3.85)	-3.3	(3.76)	(3.28)		(-0.23)	(-0.42)	
All Controls	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,447	2,447	1,558	1,558	1,558	644	644	644
R-squared	0.05	0.28	0.28	0.24	0.22	0.41	0.41	0.37

Firm-clustered robust t-statistics in parentheses. All columns include quarterly and firm fixed effects.
*** p<0.01, ** p<0.05, * p<0.1

Table 5
Effect of Financial Tweeting on Post-Announcement CARs

This table reports OLS regressions in which the dependent variable is post-announcement CAR over days [+2,+22], winsorized at the 1% level on both tails. All models restrict the sample to positive earnings surprises (earnings that beat the mean forecast). *% Financial tweets* is the percent of tweets during the measurement window that are classified as financial. *Small positive surprise* is an indicator variable set to 1 for earnings that beat the mean analyst forecast by less than two cents. All columns include quarterly and firm fixed effects, and t-statistics from firm-clustered standard errors are in parentheses.

	(1)	(2)	(3)	(4)
Dependent Variable:	Post-Announcement CAR [+2,+22]			
Surprise Type:	Positive Surprises			
% Financial Tweets during [-1,Announcement]	0.011	0.013		
	(0.70)	(0.91)		
% Financial Tweets during [+2,+22]			-0.003	0.004
			(-0.08)	(0.08)
Small positive surprise * (% Financial Tweets during [-1,+1])		-0.011		
		(-0.81)		
Small positive surprise * (% Financial Tweets during [+2,+22])				-0.013
				(-0.26)
Small positive surprise		-0.64**		-0.47*
		(2.27)		(1.85)
SUE	0.84***	0.91***	0.90***	0.96***
	(2.97)	(3.03)	(3.62)	(3.65)
Ln(Assets)	-1.43**	-1.42**	-1.52**	-1.51**
	(-2.21)	(-2.19)	(-2.46)	(-2.44)
M/B	-0.49**	-0.48**	-0.49**	-0.50**
	(-2.24)	(-2.25)	(-2.31)	(-2.33)
Cash/Assets	-0.68	-0.70	-0.16	-0.20
	(-0.37)	(-0.38)	(-0.09)	(-0.11)
Firm engages in R&D	-1.05	-0.82	-0.40	-0.23
	(-1.52)	(-1.21)	(-0.89)	(-0.53)
Firm pays Dividends	0.23	0.19	-0.21	-0.25
	(0.34)	(0.28)	(-0.32)	(-0.37)
PP&E/Assets	2.26	2.42	2.89	2.99
	(0.53)	(0.57)	(0.70)	(0.73)
Market leverage	5.78**	5.98**	6.85**	7.02**
	(2.09)	(2.16)	(2.47)	(2.53)
% Held by institutions	-0.87	-0.84	-0.69	-0.67
	(-1.20)	(-1.17)	(-0.97)	(-0.95)
Constant	19.36***	18.91***	19.10***	18.81***
	(3.99)	(3.90)	(4.15)	(4.08)
Observations	6,347	6,347	6,347	6,347
R-squared	0.23	0.23	0.23	0.24

Firm-clustered robust t-statistics in parentheses.

All columns include quarterly and firm fixed effects.

*** p<0.01, ** p<0.05, * p<0.1

Table 6
Explaining Financial Tweeting Intensity

This table reports OLS regressions in which the dependent variable is *% Financial tweets,* the percent of tweets during the measurement window that are classified as financial. *Small positive surprise* is an indicator variable set to 1 for earnings that beat the mean analyst forecast by less than two cents. *Small negative surprise* is analogous, based on earnings that miss the mean analyst earnings forecast by less than two cents. Models (4)-(6) restrict the sample to positive earnings surprises (earnings that beat the mean forecast), while Models (7)-(9) restrict the sample to negative earnings surprises (earnings the miss the mean forecast). All columns include quarterly and firm fixed effects, and t-statistics from firm-clustered standard errors are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Dependent Variable: % Financial Tweets in the given window								
Tweet Window:	[-22,-2]	[-1,Ann]	[+2,+22]	[-22,-2]	[-1,Ann]	[+2,+22]	[-22,-2]	[-1,Ann]	[+2,+22]
Sample:	All Announcements			Positive Surprises			Negative Surprises		
Positive Surprise	-0.02	1.27***	-0.02						
	(-0.09)	(2.65)	(-0.14)						
Small Positive Surprise				-0.27	0.09	0.35**			
				(-1.07)	(0.19)	(2.33)			
Small Negative Surprise							-0.39	-0.88	-0.20
							(-0.67)	(-1.09)	(-0.60)
SUE	-0.02	-0.02	-0.03**	0.10	-0.13	-0.20**	-0.02	0.01	0.02
	(-0.73)	(-0.63)	(-1.98)	(0.84)	(-0.55)	(-2.16)	(-0.58)	(0.12)	(0.77)
Ln(Assets)	-0.21	-0.39	0.32	-0.23	-2.37*	-0.53	-0.04	3.55	3.38**
	(-0.31)	(-0.39)	(0.75)	(-0.39)	(-1.75)	(-1.31)	(-0.01)	(1.34)	(2.35)
M/B	-0.11	-0.16	-0.48**	0.16	-0.50	-0.25	-1.34	-0.19	-1.45
	(-0.56)	(-0.57)	(-2.25)	(0.84)	(-1.55)	(-1.14)	(-1.64)	(-0.15)	(-1.58)
Cash/Assets	1.51	5.49**	2.09*	0.40	7.09**	0.09	7.13	4.84	4.09
	(1.00)	(2.19)	(1.91)	(0.25)	(2.11)	(0.07)	(1.19)	(0.68)	(1.14)
Firm engages in R&D	-1.18	2.46	0.72	0.69	0.42	0.11	-3.90	2.33	-2.48
	(-0.88)	(0.96)	(0.99)	(0.96)	(0.45)	(0.56)	(-1.20)	(0.43)	(-1.23)
Firm pays Dividends	0.28	0.94	0.43	0.84*	-0.82	-0.21	-2.45	2.13	0.44
	(0.49)	(0.93)	(1.35)	(1.81)	(-0.56)	(-1.48)	(-1.53)	(1.55)	(0.51)
PP&E/Assets	1.32	5.56	-0.70	2.13	-0.18	-4.06	2.11	16.48*	7.23
	(0.44)	(1.22)	(-0.22)	(0.62)	(-0.03)	(-1.07)	(0.27)	(1.69)	(0.80)
Market leverage	-1.00	0.61	-1.70	-1.03	-0.79	1.11	-7.10	1.64	-11.43**
	(-0.35)	(0.17)	(-1.37)	(-0.27)	(-0.16)	(0.86)	(-1.15)	(0.19)	(-2.51)
% Held by institutions	0.55	0.40	0.00	-0.26	0.82	0.15	2.85*	-1.37	-0.38
	(0.89)	(0.41)	(0.01)	(-0.29)	(0.73)	(0.28)	(1.96)	(-0.58)	(-0.46)
Constant	3.93	3.62	1.32	1.83	18.23*	5.73	7.44	-29.93	-20.51*
	(0.67)	(0.42)	(0.32)	(0.43)	(1.78)	(1.58)	(0.31)	(-1.50)	(-1.74)
Observations	8,836	8,836	8,836	6,347	6,347	6,347	2,489	2,489	2,489
R-squared	0.56	0.52	0.54	0.57	0.53	0.59	0.67	0.71	0.70

Firm-clustered robust t-statistics in parentheses. All columns include quarterly and firm fixed effects.

*** p<0.01, ** p<0.05, * p<0.1

Table 7
Earnings Management and Financial Tweeting Intensity
This table reports OLS regressions in which the dependent variable is *% Financial tweets,* the percent of tweets during the measurement window that are classified as financial. *Small positive surprise* is an indicator variable set to 1 for earnings that beat the mean analyst forecast by less than two cents. Models (4)-(6) restrict the sample to positive earnings surprises (earnings that beat the mean forecast. All columns include quarterly and firm fixed effects, and t-statistics from firm-clustered standard errors are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable: % Financial Tweets in given window					
Tweet Window:	[-22,-2]	[-1,Ann]	[+2,+22]	[-22,-2]	[-1,Ann]	[+2,+22]
Sample:	All EPS Observations			Positive Surprise		
Positive surprise	-0.13	1.35***	0.01			
	(-0.53)	(2.71)	(0.03)			
Positive surprise * Abs(Accruals)	3.53	-2.28	-0.72			
	(0.69)	(-0.37)	(-0.19)			
Small positive surprise				-0.23	-0.29	0.08
				(-0.64)	(-0.39)	(0.47)
Small positive surprise * Abs(Accruals)				-2.13	8.3	8.99**
				(-0.29)	(0.99)	(2.13)
Abs(Accruals)	1.24	-2.58	4.57	6.39*	-6.66	-1.15
	(0.26)	(-0.37)	(1.18)	(1.78)	(-1.16)	(-0.42)
Ln(Assets)	-0.73	-0.95	-0.04	-0.40	-2.96**	-0.45
	(-1.01)	(-0.88)	(-0.09)	(-0.63)	(-2.05)	(-0.97)
M/B	-0.13	-0.40	-0.48**	0.13	-0.62*	-0.35
	(-0.62)	(-1.27)	(-2.14)	(0.60)	(-1.74)	(-1.38)
Cash/Assets	3.01*	6.68***	2.52**	1.68	7.20**	0.91
	(1.94)	(2.61)	(2.22)	(1.05)	(2.17)	(0.71)
Firm engages in R&D	-0.87	1.36	-0.24	0.80	-0.05	0.02
	(-0.77)	(0.71)	(-0.64)	(0.99)	(-0.05)	(0.10)
Firm pays dividends	0.14	0.83	0.12	0.91*	-1.06	-0.33*
	(0.24)	(0.72)	(0.46)	(1.77)	(-0.64)	(-1.94)
PP&E/Assets	-0.47	1.32	-3.21	1.25	-5.08	-5.07
	(-0.16)	(0.28)	(-1.07)	(0.36)	(-0.81)	(-1.26)
Market leverage	-0.33	0.72	-1.34	-0.91	-2.03	0.34
	(-0.11)	(0.19)	(-1.11)	(-0.23)	(-0.39)	(0.24)
% Held by institutions	0.37	0.31	0.00	-0.47	0.89	0.35
	(0.55)	(0.29)	(0.01)	(-0.48)	(0.74)	(0.60)
Constant	7.89	10.35	5.06	3.01	24.50**	5.49
	(1.27)	(1.11)	(1.31)	(0.65)	(2.25)	(1.38)
Observations	8,836	8,836	8,836	6,347	6,347	6,347
R-squared	0.51	0.50	0.44	0.52	0.51	0.46

Firm-clustered t-statistics are in parentheses. All columns include quarterly and firm fixed effects.
*** p<0.01, ** p<0.05, * p<0.10

Table 8
Robustness – Alternate Methods of Defining Financial Tweets

This table reports OLS regressions in which the dependent variable is the announcement CAR over days [-1,+1], winsorized at the 1% level on both tails. All models restrict the sample to positive surprises (earnings that beat the mean forecast). *% Financial tweets* is the percent of tweets during the measurement window that are classified as financial. *Small positive surprise* is an indicator variable set to 1 for earnings that beat the mean analyst forecast by less than two cents. Models (1)-(2), (3)-(4), and (5)-(6) calculate financial tweets using three alternate methods. Alternate method 1 classifies tweets as "financial" if they contain the words "earning" or "conference call", method 2 additionally searches for the words "revenue" and "quarterly", while method 3 additionally searches for the words "CEO" and "CFO". All key words are included irrespective of singular or plural, but excluding occurrences in parts of words like "learning" or "yearning", etc. All columns include quarterly and firm fixed effects, and t-statistics from firm-clustered standard errors are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:			Announcement CAR [-1,+1]			
Surprise Type:	Alt. Method 1		Alt. Method 2		Alt. Method 3	
% Financial Tweets during [-1,Ann]	0.015*	0.004	0.033**	-0.004	0.017*	0.004
	(1.75)	(0.01)	(2.11)	(-0.15)	(1.91)	(0.20)
Small positive surprise * (% Financial Tweets during [-1,Ann])		0.028**		0.044***		0.025**
		(2.04)		(2.52)		(2.33)
Small positive surprise		-2.89***		-2.94***		-2.93***
		(-5.83)		(-8.07)		(-7.90)
SUE	1.59***	1.23***	1.59***	1.23***	1.59***	1.23***
	(3.92)	(3.23)	(3.92)	(3.22)	(3.93)	(3.22)
Ln(Assets)	-3.00***	-3.02***	-2.99***	-3.03***	-2.98***	-3.02***
	(-2.74)	(-2.80)	(-2.74)	(-2.82)	(-2.74)	(-2.81)
M/B	-1.24***	-1.24***	-1.24***	-1.25***	-1.24***	-1.25***
	(-4.10)	(-4.24)	(-4.10)	(-4.28)	(-4.11)	(-4.29)
Cash/Assets	-1.25	-1.03	-1.28	-1.04	-1.31	-1.09
	(-0.42)	(-0.35)	(-0.43)	(-0.35)	(-0.44)	(-0.37)
Firm engages in R&D	5.01	4.13	5.07	4.08	5.07	4.10
	(0.80)	(0.64)	(0.80)	(0.63)	(0.80)	(0.63)
Firm pays Dividends	-0.04	0.17	-0.03	0.16	-0.03	0.17
	(-0.06)	(0.21)	(-0.04)	(0.20)	(-0.03)	(0.22)
PP&E/Assets	4.29	3.82	4.22	3.65	4.20	3.66
	(0.81)	(0.75)	(0.79)	(0.71)	(0.79)	(0.71)
Market leverage	8.08**	7.33*	8.17**	7.37*	8.14**	7.42*
	(2.10)	(1.91)	(2.12)	(1.93)	(2.11)	(1.94)
% Held by institutions	0.93	0.82	0.90	0.81	0.91	0.80
	(0.77)	(0.70)	(0.75)	(0.68)	(0.76)	(0.68)
Constant	36.61***	38.25***	36.49***	38.38***	36.46***	38.31***
	(4.36)	(4.59)	(4.35)	(4.61)	(4.35)	(4.61)
Observations	6,347	6,347	6,347	6,347	6,347	6,347
R-squared	0.25	0.27	0.25	0.27	0.25	0.27

Firm-clustered robust t-statistics in parentheses.

All columns include quarterly and firm fixed effects.

*** p<0.01, ** p<0.05, * p<0.1

Figure 1
Financial Tweeting Over the Calendar Year

This figure plots the average percentage of tweets in a given calendar week that are classified as financial for all firms in our sample (left axis) and the number of earnings announcements in each calendar week for all firms in our sample (right axis).
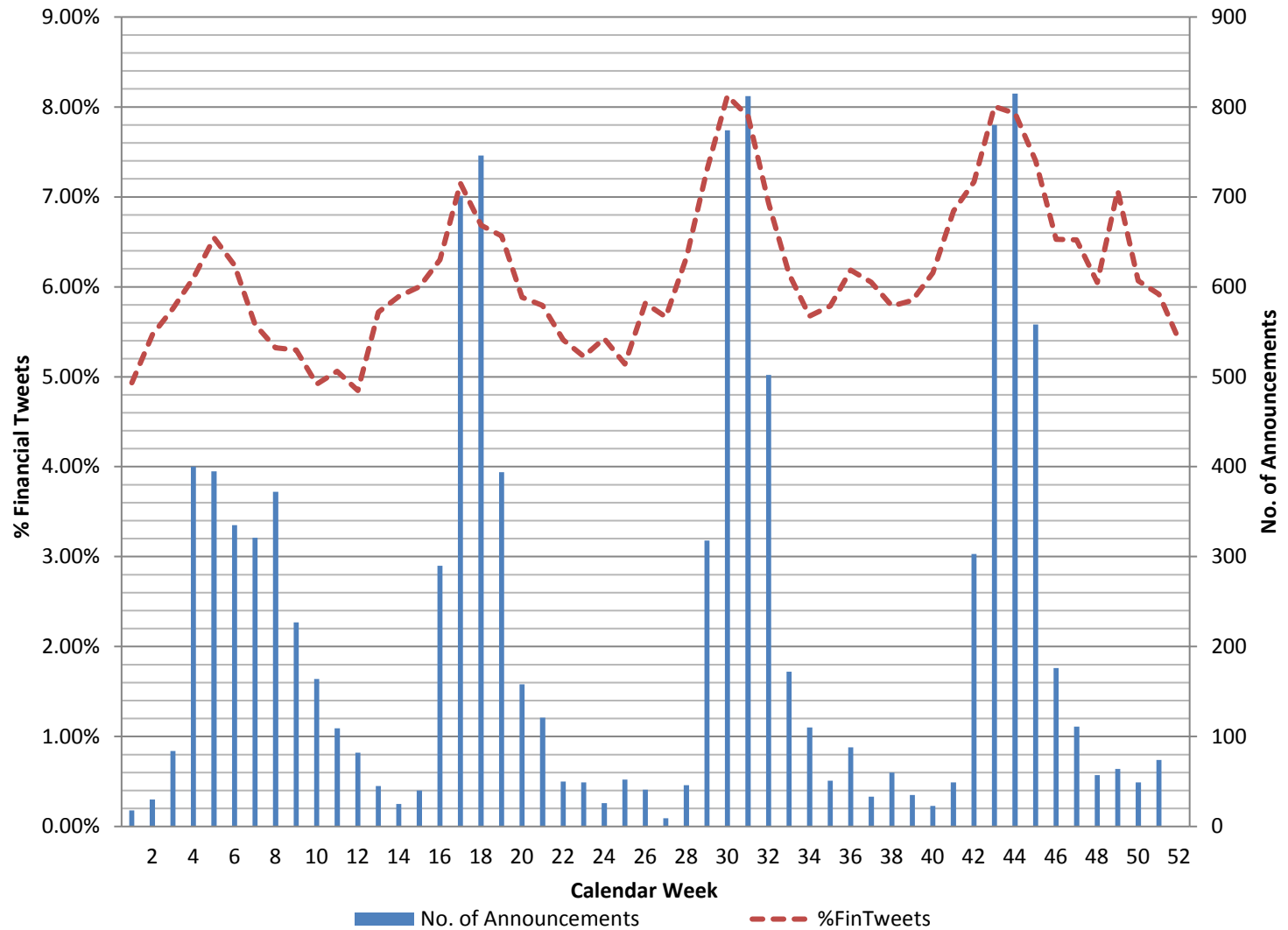
Figure 2

Adoption of Twitter by Firms, 2007-2013

This figure plots the cumulative number of firms in our sample that have created a Twitter account during or before each month over 2007-2013 (inclusive).
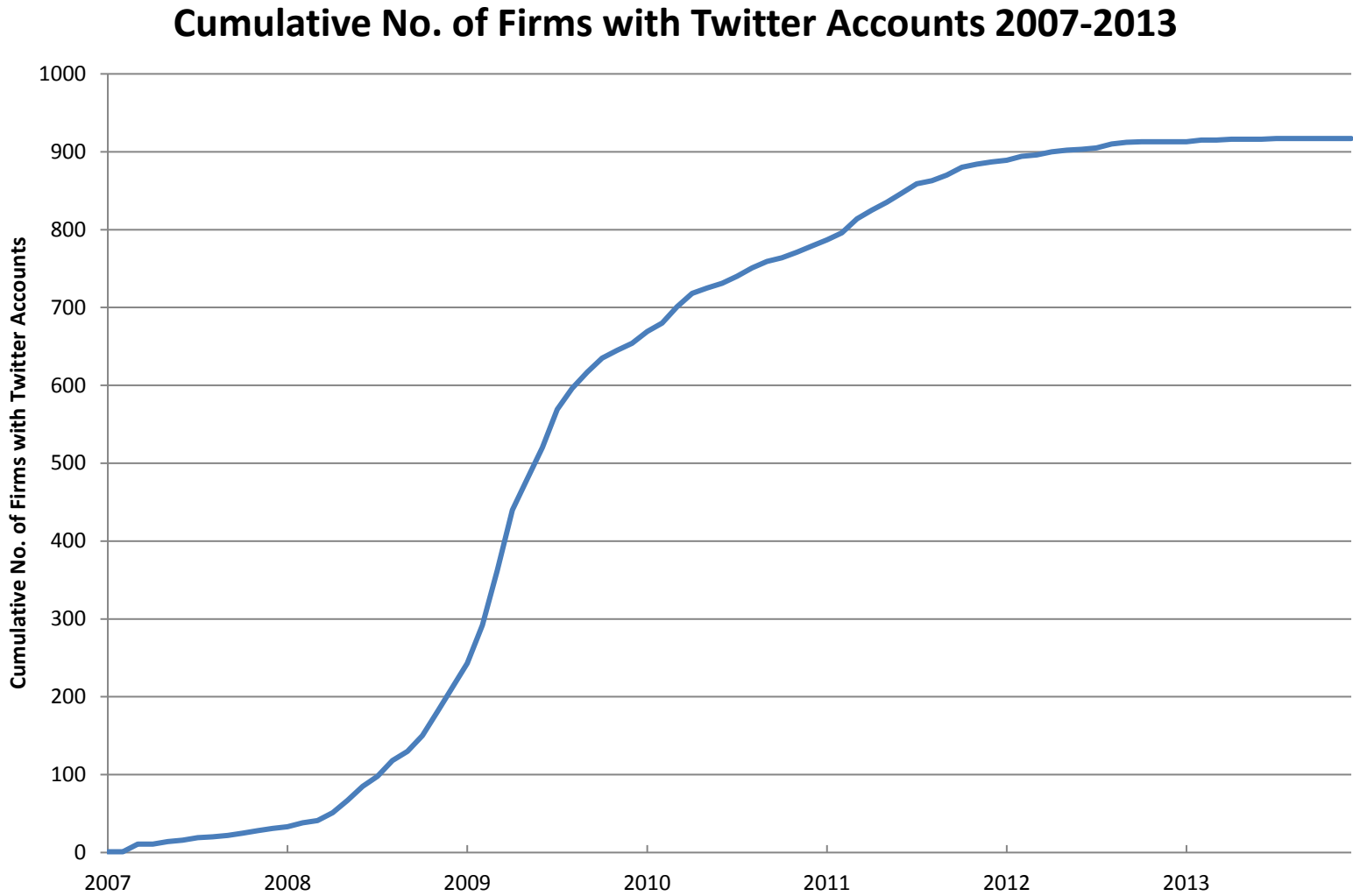

Cumulative No. of Firms with Twitter Accounts 2007-2013

Figure 3
Total Monthly Tweets by Firms, 2007-2013
This figure plots the total number of tweets made by all the firms in our sample in each month over 2007-2013 (inclusive).