Pump it Up?
Tweeting to Manage Investor Attention to Earnings News

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Abstract

We examine how firms' tweeting behavior affects earnings-news returns. For small, positive earnings surprises, greater tweeting frequency before the news release results in both more positive announcement and post-announcement returns. Targeting investors more directly during the pre-announcement window by tweeting about the impending earnings news release or tagging tweets as relevant for investors also positively correlates with announcement returns for small, positive earnings news, particularly for less visible firms. We also find that firms with a stronger history of earnings management strategically tweet based on the direction and magnitude of earnings news. Overall, we conclude Twitter provides firms an effective and strategic way to mitigate investors' limited attention, specifically when news is otherwise less likely to attract notice.

JEL classification: G14

Keywords: Social media; Twitter; Investor limited attention; Earnings news

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Abstract

We examine how firms' tweeting behavior affects earnings-news returns. For small, positive earnings surprises, greater tweeting frequency before the news release results in both more positive announcement and post-announcement returns. Targeting investors more directly during the pre-announcement window by tweeting about the impending earnings news release or tagging tweets as relevant for investors also positively correlates with announcement returns for small, positive earnings news, particularly for less visible firms. We also find that firms with a stronger history of earnings management strategically tweet based on the direction and magnitude of earnings news. Overall, we conclude Twitter provides firms an effective and strategic way to mitigate investors' limited attention, specifically when news is otherwise less likely to attract notice.

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"…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, as evidenced by post-earnings announcement drift (PEAD) in the same direction of the news (Benard and Thomas (1989,1990)). 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.[1] As investors have a limited amount of time and resources to receive, process, and react to information, security prices may not fully reflect new earnings information immediately after the information is disseminated.

The way investors obtain information, however, has changed dramatically due to the internet. By the end of the 1990s, many traditional sources of relevant information (newspapers, magazines, investment newsletters, financial services firms, the Securities and Exchange Commission (SEC), etc.) were making content readily available online. And in subsequent

[1]For evidence on investor underreaction to other types of news, see Louis and Sun (2010) and Klibanoff, Lamont, and Wizman (1998).

years, the rise of social media has allowed firms themselves to directly communicate with large numbers of people, and thus potential investors, in real time. In light of the evidence that many firms manage their earnings to meet or beat analyst forecasts (see Healy and Wahlen (1999) for a review) in order to influence their stock price, it seems plausible that firms would consider how using social media around earnings releases might affect investor reaction to such news.

This paper investigates how a firm's active use of social media affects stock price reactions to earnings news by investigating the intensity and content of a firm's tweets on the social media site Twitter. To be clear, we examine tweets made by the firm itself, not by other Twitter users about the firm. We have in mind two, non-mutually exclusive channels. Rather than ruling out one in favor of the other, we use these channels to provide a construct within which to motivate our analysis and interpret findings.

We term the first the *general attention channel*. This channel considers the potential effect of a firm's tweets regardless of content. Whether by accident or by design, a firm's tweets may affect the level of attention investors are paying to firm news, even if such news is communicated elsewhere. For example, if a firm's tweets keep the firm in the forefront of the investor's mind, even unrelated tweets by the firm may increase the likelihood an investor is "tuned in" and notices (or even seeks out) earnings news from a variety of sources and considers trading. A firm's tweets during the days following earnings news may also increase trading by prompting investors who found it inconvenient to trade when they first encountered the earnings news. Note that the *general attention channel* could be operative whether or not the firm is aware of its effect.

We term the second channel the *targeted attention channel*. In this channel, the firm purposely tweets about its earnings or earnings-related information in order to focus investor attention on its earnings news. The goal could be to simply alert the Twitter audience to earnings news, but it could also be to alter the way such news is interpreted.

Although a firm's Twitter audience likely includes some institutional investors, it is very likely to have a high proportion of potential retail investors.[2,3] Hirshleifer, Myers, Myers, and Teoh (2008) find that retail investors are net buyers after both good and bad extreme earnings news. As their evidence is based on brokerage data during 1991-1996 (before the rise of social media), it implies that retail investors notice and respond to large magnitude earnings surprises without the use of social media as an information source. Therefore, we speculate that the firm's Twitter use, which provides an additional source of information for investors, will have a greater marginal effect on investor behavior for smaller, less salient earnings surprises that would otherwise be less likely to attract significant attention through traditional channels. Accordingly, our analysis differentiates between large- and small-magnitude earnings surprises.

Our initial analysis indicates that firms with above-median tweeting frequency earn higher post-earnings announcement returns after (but not before) they become active on Twitter. This result holds after controlling for time trends and the magnitude of the earnings surprise. Moreover, it is unlikely due to a selection bias in which firms become more active tweeters, because the result is *stronger* after we control for industry fixed effects and a battery of firm-level characteristics.

Next, we refine tweeting intensity to be measured during the days preceding, during, or following the announcement news release window. Tweeting intensity during any of these windows has no significant correlation with earnings announcement returns for negative earn-

[2]To justify our speculation that a firm's Twitter audience is skewed toward a retail audience, 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.

[3]Multiple papers establish that retail traders can move prices. For example, see Barber and Odean (2008), Barber, Odean, and Zhu (2009), Burch, Emery, and Fuerst (2014), Hvidkjaer (2008), and Kumar and Lee (2006).

ings surprises, regardless of the surprise magnitude. For small-magnitude positive surprises, however, we find that higher levels of tweeting during any of the three windows (before, during, or after the announcement period) are associated with higher post-announcement returns.

It is possible that positive return reactions to earnings news cause firms to tweet more often in response (e.g., in response to congratulatory tweets from others). Under this direction of reverse causality, however, we would expect strong correlation between firm tweeting intensity and earnings returns when earnings surprises are the most positive (thus generating the most positive announcement returns). Against this prediction, for the subsample of larger-magnitude positive earnings surprises we find no significant correlation between tweeting frequency and announcement returns. It is only for small positive surprises that tweeting before, during, or after the earnings announcement window are all associated with higher post-announcement returns. Moreover, two of the three tweeting windows over which we measure tweeting intensity end before the post-announcement return window begins, which is difficult to reconcile with reverse causality.

Overall, we conclude the evidence supports the *general attention channel* for small, positive earnings surprises. To investigate the *targeted attention channel*, we measure the percent of the firm's tweets that are explicitly financial in nature and thus appear to be directed toward investors. A greater portion of financial tweets during the few weeks before (or during the few days surrounding) earnings releases is associated with higher announcement returns, but once again only for small-magnitude positive earnings news. To corroborate the notion that tweeting has a larger impact when news is otherwise less likely to gain attention, we split the sample into high and low visibility firms for which news is presumably more or less likely to be noticed. Regardless of whether we proxy for visibility with the firm's market capitalization or level of analyst coverage, the effect of tweeting on earnings returns is stronger for less visible firms.

That tweeting matters more for less visible news also provides a potential explanation for why tweeting impacts returns for small-magnitude positive earnings news but not for small-magnitude negative news. Consistent with the measures many firms take to avoid it, falling short of earnings expectations, even by a small amount, is much more likely to attract attention and significantly move prices than beating expectations by a similar amount. Thus, on the margin, tweeting is less likely to matter for small negative news than for small positive news. To buttress this potential explanation, we document that announcement returns following small-magnitude earnings results are much larger in magnitude for small negative earnings news than for small positive news.

The contrast in results for positive and negative earnings results prompts us to investigate the possibility that some 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 tweet accordingly. We document that financial tweeting intensity during the three-day window surrounding earnings news is higher for positive earnings news than for negative news. We also find that within the sample of positive news observations, financial tweeting intensity during the *post-announcement* window is higher for small-magnitude earnings news than for large-magnitude news. Given our earlier evidence, this result suggests that firms attempt to focus investor attention on positive earnings news exactly when focus-increasing efforts are more likely to affect post-announcement returns. Interestingly, we find this evidence of strategic tweeting is stronger for firms that more often engage in earnings management.

Our results imply that a firm's social media audience includes investors, even if the content is not aimed at the financial community specifically, and that social media impacts the way in which stock prices respond to earnings news. In particular, Twitter offers firms a strategic tool to manage the reaction of their stocks to corporate news, and we document evidence consistent with some firms strategically tweeting around their earnings news. 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. Our findings suggest the SEC should monitor closely the evolution of corporate social media use and its impact on stock prices.

2. The Rise of Twitter and Social Media's Impact on Investors

Twitter was created in 2006, and the year 2009 marked a major increase 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)). Growth in Twitter accounts is plotted in Figure 1. In Figure 2 we plot 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.

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.[4] 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. In addition, the content of firms' tweets shows that firms change their tweeting behavior around earnings results. As shown in Figure 4, there is a strong seasonal pattern within the calender year in

[4] 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 December 2013. However, there are also firms without a large retail consumer market that actively tweet, such as Alcoa.

the percent of tweets that are financial (defined later), and these financial tweets correlate strongly with earnings seasons.

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 (2013) find that tweeting by CEOs and CFOs provides incremental information that both predicts returns and increases liquidity. Both of these papers find stronger effects for smaller, less visible firms. 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.[5] 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.

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 fiscal years 2004 through 2013. From the Thomson-Reuters Institutional

[5] 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.

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.[6] 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 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.[7]

Using the starting date of the firm's Twitter account, we define an indicator variable *Post Twitter* that takes the value 1 for all earnings announcements at least one quarter after the start date of the firm's first Twitter account, and 0 otherwise. If a firm has more than one account, we use the starting date of its earliest account when coding *Post Twitter*.

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. In total, we collect over 3.4 million tweets over the 2007-2013 time period, from which we tabulate the number of tweets each firm made every day from the time of its account creation. For firms that have multiple accounts, since 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.[8] Using this daily count of tweets, for each firm's quarterly earnings

[6] 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.

[7] 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.

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

announcement we tabulate the number of tweets over three trading-day windows around the announcement date: [-20,-2], [-1,+1], and [+2,+30].

In addition, we classify each tweet based on whether it is financial in nature, which we define as containing the word "earning" or "conference call" (irrespective of capitalization and whether singular or plural), or containing a "hashtag" 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 "$AAPL" (where "$" is contiguously followed by the stock ticker to construct the hashtag). 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 symbol as financial tweets.[9] 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.

Quarterly earnings announcement dates are from the I/B/E/S database during the years 2004-2013.[10] For each EPS announcement, from CRSP we obtain returns from +2 to +60 trading days after the announcement to measure post-announcement returns, which follows papers such as Foster, Olsen, and Shevlin (1984) and Bernard and Thomas (1989). 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

[9] 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

[10] We include earnings prior to Twitter's establishment in 2006 in order to have a more balanced sample of quarterly earnings observations both before and after a firm becomes active on Twitter for our initial analysis.

and bottom 1%. The final sample contains 918 firms with Twitter accounts and 23,439 EPS observations for these firms.

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. Each quarter, we use the prior quarter's SUE values to form terciles of SUE.[11] In addition, for each announcement we calculate the announcement CAR over trading days [-1,+1], winsorized at the top and bottom 1% level.

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.[12] 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 $8.8 billion (median value is $1.2 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 billion as opposed to $5.5 billion). In addition, above-median tweeters have a slightly higher market-to-book ratio (2.30 versus 1.98) but are less likely to engage in R&D activity (51% versus 63%). Above-median and below-median tweeting firms have statistically similar levels of cash/assets, tangible assets, market leverage and institutional holdings, and are equally likely to pay dividends (about 43%). Above-median tweeting firms tweet about five times during the announcement window (trading days [-1,+1]) versus less than one tweet on

[11] Grouping SUE observations into terciles, as opposed to quintiles, limits the number of interaction terms needed in our cross-sectional regressions and thus eases exposition. Our results are robust to using quintiles instead, however.

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

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 the general attention channel

To begin, our initial analysis investigates whether firms that are more active on Twitter with general tweeting (regardless of content) have different post-announcement returns than those that are less active. Specifically, we take a difference-in-difference approach and analyze the difference in post-announcement abnormal returns before and after Twitter account creation for firms that are above-median in their tweeting intensity versus those that are below-median tweeters. We thus define an indicator variable *Post-Twitter account creation* that is set to 1 if the firm has created a Twitter account at least one month prior to the earnings announcement observation date. In order to discern the effect of different levels of Twitter-use intensity, we code the indicator variable *Above-median tweeter* as 1 if the firm is above the sample median number of total tweets during the years 2012-2013. Hence, this variable classifies firms based on whether they are the more active tweeters by the end of the sample period. Our later analysis more precisely measures tweeting intensity around individual earnings announcements.

Table 2 reports difference-in-difference OLS regressions in which the dependent variable is the size/BM adjusted post-announcement CAR over days [+2,+60] for every firm-quarter earnings announcement (winsorized at the 1% level). All models include fixed effects for each quarter, so that no results are driven by a potential time trend in post-earnings announcement returns. T-statistics are adjusted for heteroskedasticity. The first coefficient of interest is that for *Post-Twitter account creation*, which measures whether post-earnings announcement returns differ after a firm becomes active on Twitter. The second coefficient of interest is that on the interaction between *Post-Twitter account creation* and *Above-median tweeter*, i.e., (*Post Twitter*)*(*Above-median tweeter*), which measures whether post-announcement returns differ after account creation for firms that become more active in their Twitter use.

The results in Model (1) indicate that on average, there is no difference in post-announcement CARs before and after opening a Twitter account. However, Model (2) indicates that there is a significant difference before and after account creation for above- versus below-median tweeters. Sample means and the coefficients imply that the predicted post-announcement CAR for above-median tweeters is 1.14% before Twitter account creation, 1.67% after creation, and that the interaction term (*Post Twitter*)*(*Above-median tweeter*) is highly significant (t-statistic = 3.49).

Model (3) repeats the specification but includes the firm-level control variables (measured at the latest possible date prior to at least 30 days before the earnings announcement), as well as industry fixed effects (Fama–French 49 industry indicators).[13] Note that the coefficient on (*Post Twitter*)*(*Above-median tweeter*) is even larger at 1.67, as is the t-statistic at 3.76. Thus, even if the firm variables and industry fixed effects we include do not perfectly control for firm characteristics, it seems very unlikely that firm characteristics explain the result of interest. Results are *stronger* after including variables that (at least partially) control for such firm characteristics.

Models (4)-(6) show the result is unchanged after additionally controlling for the magnitude of the earnings surprise (*SUE*). In untabulated results we replace *Above-median tweeter* (wherever it appears in each model) with a similarly defined *Above-median followers* indicator variable based on the number of Twitter accounts following the firm's tweets during

[13] It is not possible to include firm fixed effects, because the variable *Above-median tweeter* has a constant value for each firm's entire time series, and would thus be collinear with firm fixed effects. However, in subsequent analysis we are able to use firm fixed effects.

2012-2013. Results are very similar,[14] which is not surprising given that the sample correlation between the natural log of tweeting frequency and that of the number of followers is 0.66.

Table 2 thus suggests that the *general attention channel* may be operative, as there is a significant correlation between the creation and usage of Twitter by a firm and the magnitude of post-announcement CARs. In particular, firms with above-median Twitter use experience higher post-announcement CARs than below-median tweeters, but only after they become active on Twitter.

Although at this stage in the analysis it would be too strong to infer causality,[15] this preliminary result leads us to investigate further to understand more about the circumstances in which tweeting seems to matter. We next limit the sample to earnings observations that occur after a firm creates a Twitter account, and refine our metric of tweeting intensity to measure the number of tweets during the days immediately before and surrounding the earnings announcement. We also classify *SUE* observations into terciles, so we can investigate whether tweeting affects returns differently based on the magnitude of the earnings surprise.

Panel A of Table 3 reports OLS regressions in which the dependent variable is the size/BM adjusted announcement CAR over days [-1,+1] for every firm-quarter earnings announcement (winsorized at the 1% level). The main independent variable of interest is *Ln(1+No. of tweets)*, the natural log of one plus the number of tweets the firm makes over various windows around the earnings announcement. All models include quarterly fixed effects and firm characteristics as before, and since these regressions do not include any variables that remain constant for each firm's time series of observations, we are additionally able to include firm fixed effects. We can thus interpret the coefficients as the average

[14] E.g., the coefficient and t-statistic for (*Post twitter*)*(*Above-median followers*) in both Models (3) and (6) are 1.14 and 3.13, respectively.

[15] Possibly an uncontrolled for firm-specific trend in some firms simultaneously leads to both Twitter adoption and higher post-announcement returns.

within-firm time-series differences in the effect of tweeting on announcement returns, which mitigates concerns that the results are driven by a firm-level selection bias in which firms become more active on Twitter.

Two of the specifications we report test whether the association between tweeting frequency and announcement returns differs between different magnitudes of *SUE* observations. We note that tercile 1 observations contain only negative *SUE* observations, while tercile 3 observations contain only positive *SUE* observations. Tercile 2 contains both negative and positive observations, and consists of the smallest absolute magnitude observations.

The results in Model (1) indicate that more frequent tweeting during the [-20,-2] trading-day window prior to the earnings announcement has no effect on the announcement CAR overall, as *Ln(1+No. of tweets)* is insignificant. Model (2) shows the association between announcement CAR and *Ln(1+No. of tweets)* does not statistically differ between *SUE* terciles, as both of the coefficients on the interactions between the *SUE* tercile indicators and *Ln(1+No. of tweets)* are insignificant.

Model (3) indicates that tweeting frequency during the [-1,+1] announcement window is positively correlated with announcement CARs. Model (4) shows there are no statistically significant differences in this effect across the *SUE* tercile groups. Although Model (3) shows tweeting and announcement CARs are positively correlated, we caution against making a strong causal inference because possibly more positive market reactions to earnings news lead firms to tweet more frequently. We are able to make stronger causal inferences later below.

In Panel B of Table 3, we investigate the effect of tweeting on *post-announcement* CARs. Although Models (1), (3), and (5) do not show that tweeting frequency correlates with post-announcement returns for the overall sample, Models (2), (4), and (6) show that post-announcement returns are higher with more frequent tweeting for tercile 2 *SUE* observations.

This is consistent with the notion that publicity through Twitter has the greatest impact for smaller-magnitude earnings which are otherwise less likely to be noticed. To give some sense of the economic magnitude, for Tercile 2, the coefficients imply that after controlling for the level of *SUE* itself, a one-standard deviation (SD) increase in the number of tweets during trading days [-1,+1] is associated with a 0.77% absolute higher post-announcement CAR (from an average of 0.06% to 0.83%).

The results in Panel B also more strongly suggest a causal impact of tweeting on returns, for two reasons. First, if more positive stock market reactions to earnings announcements lead firms to tweet more often (i.e., if reverse causality explains the positive correlation between tweeting frequency and returns), we would expect the *most* positive returns to lead to the most tweets and thus expect significant correlation between returns and tweeting frequency for Tercile 3 *SUE* observations. Instead, it is only Tercile 2 observations that have a significant correlation. Second, in Models (2) and (4) the windows over which tweets are measured end before the post-announcement return measurement window begins, which is difficult to reconcile with a reverse causality mechanism in which returns lead to more tweeting.

Overall, the results in Table 3 suggest that general tweeting frequency contemporaneously correlates with announcement returns, and more interestingly, even predicts more positive post-announcement returns for smaller-magnitude earnings surprises. The second result is consistent with tweeting helping to focus the attention of investors when the earnings results themselves are less likely to attract as much notice. We now explore this result in further detail. In particular, we investigate whether tweeting has differential effects on returns for small negative versus small positive earnings surprises.

Table 4 reports the results of additional regressions that explain post-announcement returns (size/BM-adjusted post-announcement CARs over days [+2,+60]). As before, CARs are winsorized at the 1% level, and all models include quarterly and firm fixed effects. The main independent variables are *Ln(1+No. of tweets)*, measured over various windows, *Small positive surprise*, *Small negative surprise*, and interactions between *Ln(1+No. of tweets)* and either *Small positive surprise* or *Small negative surprise*. 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 6,679 observations in the positive earnings surprise subsample, 34% 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 2,766 observations in the negative earnings surprise subsample, 33% have *Small negative surprise* coded as 1.

Models (1) to (3) restrict the sample to positive earnings surprises only, using the indicator *Small positive surprise* to distinguish small from large positive surprises. The positive significance on *Small positive surprise* * *Ln(1+No. of tweets)* indicates that post-announcement returns are significantly higher when the firm tweets more frequently around smaller-magnitude earnings results. For example, for small positive surprises a one-SD increase in the number of tweets during the [-1,+1] window around the earnings announcement increases the post-announcement CAR from an average 1.61% to an average 2.64%. However, for large positive surprises, the same increase in tweeting frequency is associated with a statistically insignificant *decline* in post-announcement CARs of 0.31%. As the t-statistics on *Small positive surprise* * *Ln(1+No. of Tweets)* imply, the difference in the marginal effect for small positive versus large positive surprises is statistically significant at the 5% level in Model (1), and at the 1% level in Models (2) and (3).

It is important to note that the specifications control for the magnitude of the earnings news itself, not only by including *Small positive surprise*, but also *SUE*. In untabulated results we replace *SUE* (which is the surprise standardized by the pre-announcement stock price) with the raw (not standardized) surprise, and results are substantially unchanged.

Models (4)-(6) limit the sample to negative surprises. For these observations, we do not find that tweeting frequency is associated with significantly different post-announcement CARs regardless of the surprise magnitude.

In addition to showing that tweeting impacts post-announcement returns, the results in Table 4 are interesting for two reasons. First, they document that the return-impact of tweeting is larger for smaller-magnitude earnings news. These earnings announcements are less salient on their own, and it seems the marginal impact of increasing investor attention through tweeting is accordingly greater. Second, the finding that tweeting impacts returns following positive but not negative earnings news highlights the possibility that firms could also tweet differently based on the direction and magnitude of earnings in order to positively influence returns. We defer our investigation of strategic tweeting to section 4.4.

4.2. Evidence on the targeted attention channel

Thus far we have analyzed the return impact of tweeting without regard to tweet content. Although general tweeting draws attention to the firm and in turn could increase investor attention to all relevant news (including earnings results), it is not the most direct way firms would tweet to purposefully focus investor attention on financial news. In this section we examine the impact of tweets that are both close in time to the earnings release and financial in their content. Such tweets are more likely to have a direct goal of targeting investors. As discussed earlier, we identify financial tweets as those referring to the earnings news release or having a hashtag with the stock's ticker symbol, meaning the firm has flagged the tweet as relevant to investors. We then measure the percentage of tweets that are financial during various windows around the earnings release (*% Financial tweets*), and analyze how the percentage of financial tweets relates to announcement and post-announcement returns.

Just as Table 3 initially documents potential correlation between general tweeting frequency and announcement returns (size/BM adjusted announcement CAR over days [-1,+1]), our analysis of *% Financial tweets* also begins with announcement returns, and motivated by earlier findings, we once again report separate results for positive and negative earnings news. All specifications continue to include firm and quarterly fixed effects.

In Models (1) and (2) of Table 5 for positive earnings news, the coefficient on *% Financial tweets* is statistically insignificant and thus fails to indicate that the percentage of financial tweets correlates with announcement returns in general. However, once again we observe significant results for smaller-magnitude earnings news. In Model (1), the coefficient on the interaction between *Small positive surprise* and *% Financial tweets* is positive and statistically significant at the 5% level, and 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 0.51% to 1.21%. The effect is similar in Model (2), with a one-SD increase in the percentage of financial tweets associated with an increase in CAR from 0.55% to 0.99% for small positive surprises. As with earlier results, Models (3) and (4) do not show significant results for negative surprises, as the *% Financial tweets* variables are insignificant. Thus, for small-magnitude positive (but not negative) earnings news, greater financial tweeting intensity before the announcement window predicts higher announcement returns, and greater tweeting frequency also contemporaneously correlates with announcement returns.

To further corroborate the notion that tweeting matters more for news that is otherwise less likely to attract attention, in Models (5)-(8) we repeat Model (1) for positive earnings surprises but sort the sample into low and high visibility firms. We expect that financial tweeting will have a greater impact for low visibility firms, and the models confirm this expectation. Models (5) and (6) 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 (5) sample) have lower visibility, for example, in that they attract less media coverage (Fang and Peress (2009)). In Models (7) and (8) we split the sample based on the number of analysts that issued earnings forecasts 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 (5) and (7) (the low visibility samples) but insignificant in Models (6) and (8) (the high visibility samples). These results are consistent with Blankespoor, Miller, and White (2014) and Chen, Hwang, and Liu (2013) in finding tweeting's impact is stronger for less visible firms.

Unlike for general tweeting, in untabulated results we do not find that the level of financial tweeting before or during the announcement window is correlated with *post-announcement* returns for small positive earnings results. This is perhaps not surprising, because specifically increasing investor attention before or during the period in which positive earnings news is announced should presumably help mitigate any underreaction to such positive news (thus causing a more positive announcement reaction).

In summary, Table 5 provides evidence 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.

Taking the results in Tables 4 and 5 together, we find that a greater number of tweets in general, as well as financial tweets in particular, is associated with higher earnings-related returns. Thus, for small positive earnings surprises, the evidence supports both the *general attention channel* and the *targeted attention channel*. Whereas general tweeting frequency is positively associated with higher post-announcement returns following small positive surprises, financial tweeting, which is more targeted to investors, is associated with higher announcement returns in reaction to such news.

4.3. Small negative versus small positive earnings surprises

In this section we briefly comment on why tweeting impacts the returns for small, positive earnings news but not small, negative earnings news. We conjecture this is because missing earnings by a small amount is much bigger news, thus attracting more attention, than beating earnings by a similar amount. This conjecture is consistent with the accruals literature that documents that firms manage earnings to avoid falling short of earnings expectations.

It is also consistent with the announcement reaction to small positive earnings surprises in our sample. In untabulated results, for the sample used in Table (5), the mean and median abnormal announcement return for small, positive earnings news are 0.52% and 0.41%, respectively, while for small, negative earnings news the mean and median are -2.70% and -2.29%, respectively. We confirm through regression analysis that this difference is not due to the possibility that firms missing their earnings expectations have lower expected earnings (which would result in a one- or two-cent result below expected earnings being a larger-magnitude result on a percent basis compared to beating earnings by the same absolute amount). Given these results, as well as the conventional motivation offered for earnings management, it is not surprising that tweeting impacts returns for small positive but not small negative earnings news.

4.4. Do firms tweet strategically?

Although the focus of our paper is on how market prices react to earnings news conditional on the firm's tweeting activity, as noted earlier, we also 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* 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) and (4)). However, financial tweeting intensity during the *announcement* window is stronger for positive earnings news in Model (2), as the average financial tweeting intensity increases from 4.14% to 5.39% when earnings news is positive. And within the sample of positive earnings surprises, Model (6) implies that the average financial tweeting intensity during the post-announcement window increases from 0.71% to 1.15% 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.

Finally, we examine whether the evidence of strategic tweeting is stronger for firms that seem to engage more heavily in earnings management. To measure the firm's 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). We repeat the regressions and include the absolute value of accruals, $Abs(Accruals)$, as well as its interaction with either *Positive surprise* (Models (7)-(8)) or *Small positive surprise* (Models (10)-(12)). Model (8), which repeats the specification in Model (2), 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 (12), however, which repeats the specification in Model (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 manipulate their earnings results are also more likely to strategically tweet following these results.

4.5. 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.

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 returns by presumably affecting investors' attention levels. We find that tweeting intensity is positively associated with returns for positive earnings news, but only for small-magnitude earnings results. This is consistent with tweeting having a greater effect on investor attention when the earnings themselves are less likely to garner attention. Tweets that are specifically financial in nature have similar return impacts for small, positive earnings news, and these results are stronger for less visible firms. There is some evidence that firms tweet strategically by increasing the intensity of such financial tweets during and after the release of positive earnings results, suggesting they are aware of the impact such tweeting can have. Overall, Twitter impacts stock returns for positive earnings news that is less likely to be noticed, and at least some firms seem to take advantage.

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Table 1

Summary Statistics

This table reports summary statistics for the sample of firm-quarter earnings announcements over 2004-2013. 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. *% Financial tweets* is the percent of tweets during the measurement window that are classified as financial.

	All Firm/Quarters N=21,224		Below Median N=8,948		Above Median N=11,585	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Announcement CAR [-1,+1]	0.52	8.73	0.41	8.85	0.65	8.59
Post-announcement CAR [+2,+60]	1.18	16.27	1.08	17.39	1.22	15.34
SUE	0.03	0.47	0.02	0.44	0.05	0.48
Post-Twitter account creation	0.46	0.50	0.42	0.49	0.49	0.50
Small positive surprise	0.24	0.42	0.21	0.41	0.26	0.44
Small negative surprise	0.10	0.29	0.10	0.30	0.09	0.29
Book Assets	8,805	24,874	5,593	20,669	11,098	27,295
M/B	2.15	1.41	1.98	1.30	2.30	1.48
Cash/Assets	0.22	0.21	0.22	0.23	0.21	0.19
Firm engages in R&D	0.56	0.50	0.63	0.48	0.51	0.50
Firm pays dividends	0.43	0.50	0.42	0.49	0.44	0.50
PP&E/Assets	0.34	0.24	0.33	0.23	0.34	0.25
Market leverage	0.12	0.14	0.14	0.15	0.11	0.13
% Held by institutions	0.65	0.28	0.63	0.29	0.68	0.26
Number of tweets [-20,-2]	16.31	46.30	2.93	9.29	27.62	59.82
Number of tweets [-1,+1]	3.37	9.07	0.77	2.73	5.57	11.59
Number of tweets [+2,+30]	25.71	70.90	4.61	15.79	43.54	91.19
% Financial tweets [-20,-2]	2.05	11.03	5.20	17.82	0.49	4.17
% Financial tweets [-1,+1]	4.94	16.82	9.93	24.42	2.81	11.59
% Financial tweets [+2,+30]	0.97	7.57	2.11	11.89	0.37	3.59

Table 2

Post-Announcement CARs Before and After Twitter Account Creation

This table reports OLS regressions in which the dependent variable is the size/BM adjusted post-announcement CAR over days [+2,+60], winsorized at the 1% level on both tails. *Post Twitter account creation* is an indicator variable set to 1 if firm has created a Twitter account at least one month prior to the earnings announcement observation date. *Above-median tweeter* is an indicator variable set to 1 for those firms that are above the median number of tweets firms made during 2012-2013. *SUE* is a standardized unexpected earnings measure, which measures the direction and magnitude of the earnings news surprise. All specifications include industry (Fama-French 49) and quarterly fixed effects, and t-statistics from heteroskedasticity-robust standard errors are in parentheses.

Dependent Variable: Size/BM Adjusted Post-Announcement CAR [+2,+60]						
	(1)	(2)	(3)	(4)	(5)	(6)
Post-Twitter account creation	0.21	-1.01*	-0.92*	0.19	-1.01*	-0.92*
	(0.46)	(-1.95)	(-1.75)	(0.43)	(-1.95)	(-1.76)
(Post Twitter) * (Above-median tweeter)		1.55***	1.67***		1.54***	1.66***
		(3.49)	(3.76)		(3.46)	(3.74)
Above-median tweeter		-0.55*	0.56*		-0.53*	0.56*
		(-1.82)	(1.74)		(-1.75)	(1.72)
SUE				-0.21***	-0.23***	-0.20***
				(-2.79)	(-2.92)	(-2.58)
Ln(Assets)	-0.47***		-0.57***	-0.46***		-0.56***
	(-6.60)		(-7.57)	(-6.46)		(-7.43)
M/B	-0.20*		-0.24**	-0.20*		-0.24**
	(-1.87)		(-2.27)	(-1.90)		(-2.29)
Cash/Assets	2.61***		2.67***	2.64***		2.69***
	(2.97)		(2.98)	(3.01)		(3.00)
Firm engages in R&D	1.01***		0.96**	1.02***		0.97**
	(2.61)		(2.44)	(2.65)		(2.46)
Firm pays dividends	-0.04		-0.09	-0.02		-0.08
	(-0.16)		(-0.34)	(-0.08)		(-0.28)
PP&E/Assets	3.07***		3.51***	3.06***		3.49***
	(3.89)		(4.34)	(3.88)		(4.32)
Market leverage	6.35***		7.37***	6.12***		7.14***
	(5.46)		(6.14)	(5.27)		(5.95)
% Held by institutions	-1.53***		-1.71***	-1.44***		-1.61***
	(-3.37)		(-3.66)	(-3.16)		(-3.45)
Constant	6.93***	1.69***	7.04***	6.83***	1.67***	6.95***
	(4.14)	(6.16)	(4.09)	(4.08)	(6.08)	(4.04)
Observations	22,756	22,026	22,026	22,756	22,026	22,026
R-squared	0.04	0.03	0.04	0.04	0.03	0.04
Industry (FF49) fixed effects	Yes	No	Yes	Yes	No	Yes
Quarterly fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Heteroskedasticity-robust t-statistics are in parentheses.

*** p<0.01, ** p<0.05, * p<0.10

Table 3

Tweeting Around the Announcement Window and CARs

This table reports OLS regressions in which the dependent variable is either the announcement CAR over days [-1,+1] (Panel A), or the post-announcement CAR over days [+2,+60] (Panel B). CARs are winsorized at the 1% level on both tails. *Ln*(*1+No. of tweets*) is the natural log of the number of tweets the firm makes over a given window around the announcement. *SUE* is a standardized unexpected earnings measure, which measures the direction and magnitude of the earnings news surprise. *SUE tercile 1* is an indicator variable set to 1 for the most negative *SUE* observations (those in the lowest tercile). Likewise, *SUE tercile 3* indicates the most positive observations, and *SUE tercile 2* indicates the middle tercile (which contains smaller-magnitude observations of both signs). All specifications include quarterly and firm fixed effects, and t-statistics from heteroskedasticity-robust standard errors are in parentheses.

Panel A: Earnings Announcement CARs and Tweeting Around the Earnings Announcement Window

Dependent Variable: Size/BM Adjusted Announcement CAR [-1,+1]

	(1)	(2)	(3)	(4)
Tweet Window:	No. of Tweets [-20,-2]		No. of Tweets [-1,+1]	
Ln(1+No. of tweets)	0.08	-0.07	0.31***	0.05
	(0.88)	(-0.60)	(2.76)	(0.34)
(SUE tercile 2) * Ln(1+No. of tweets)		0.17		0.24
		(1.47)		(1.50)
(SUE tercile 3) * Ln(1+No. of tweets)		0.15		0.30
		(1.13)		(1.62)
SUE tercile 2		3.32***		3.39***
		(8.72)		(10.15)
SUE tercile 3		7.02***		6.95***
		(17.25)		(18.82)
SUE	0.41***	0.06	0.41***	0.06
	(4.87)	(0.81)	(4.89)	(0.84)
Ln(Assets)	-3.50***	-3.00***	-3.56***	-3.04***
	(-6.09)	(-5.39)	(-6.19)	(-5.47)
M/B	-1.39***	-1.17***	-1.40***	-1.18***
	(-6.39)	(-5.56)	(-6.43)	(-5.58)
Cash/Assets	-1.74	-1.12	-1.87	-1.20
	(-1.01)	(-0.67)	(-1.08)	(-0.72)
Firm engages in R&D	1.65	0.76	1.75	0.82
	(1.13)	(0.55)	(1.19)	(0.60)
Firm pays dividends	-0.62	0.01	-0.63	-0.00
	(-1.26)	(0.02)	(-1.28)	(-0.00)
PP&E/Assets	-2.58	-1.43	-2.54	-1.41
	(-0.79)	(-0.46)	(-0.78)	(-0.46)
Market leverage	11.24***	9.06***	11.23***	9.07***
	(4.50)	(3.85)	(4.49)	(3.86)
% Held by institutions	0.76	0.51	0.74	0.47
	(1.27)	(0.88)	(1.22)	(0.82)
Constant	28.71***	20.64***	29.38***	21.10***
	(5.86)	(4.37)	(6.00)	(4.49)
Observations	10,493	10,493	10,493	10,493
R-squared	0.13	0.21	0.13	0.21

Heteroskedasticity-robust t-statistics are in parentheses. All columns include quarterly and firm fixed effects.

*** p<0.01, ** p<0.05, * p<0.10

Panel B: Post-Earnings Announcement CARs and Tweeting Around the Earnings Announcement Window

	Dependent Variable: Size/BM Adjusted Post-Announcement CAR [+2,+60]					
	(1)	(2)	(3)	(4)	(5)	(6)
Tweet Window:	No. of Tweets [-20,-2]		No. of Tweets [-1,+1]		No. of Tweets [+2,+30]	
Ln(1+No. of tweets)	0.11	-0.08	-0.00	-0.27	0.16	-0.07
	(0.66)	(-0.35)	(-0.01)	(-0.93)	(1.02)	(-0.33)
(SUE tercile 2) * Ln(1+No. of tweets)		0.51**		0.72**		0.55***
		(2.35)		(2.44)		(2.76)
(SUE tercile 3) * Ln(1+No. of tweets)		-0.08		-0.13		0.03
		(-0.32)		(-0.36)		(0.11)
SUE tercile 2		-2.24***		-2.02***		-2.56***
		(-3.17)		(-3.26)		(-3.49)
SUE tercile 3		0.56		0.55		0.30
		(0.69)		(0.77)		(0.36)
SUE	-0.25**	-0.26**	-0.25**	-0.26**	-0.25**	-0.26**
	(-2.14)	(-2.21)	(-2.14)	(-2.22)	(-2.14)	(-2.19)
Ln(Assets)	-8.61***	-8.71***	-8.57***	-8.65***	-8.62***	-8.71***
	(-8.14)	(-8.22)	(-8.11)	(-8.17)	(-8.16)	(-8.22)
M/B	-2.76***	-2.73***	-2.76***	-2.73***	-2.75***	-2.72***
	(-6.99)	(-6.91)	(-6.99)	(-6.91)	(-6.98)	(-6.89)
Cash/Assets	1.71	1.83	1.77	1.89	1.65	1.77
	(0.55)	(0.59)	(0.57)	(0.61)	(0.53)	(0.57)
Firm engages in R&D	-5.51*	-5.56*	-5.59*	-5.70*	-5.45*	-5.52*
	(-1.69)	(-1.71)	(-1.72)	(-1.76)	(-1.68)	(-1.70)
Firm pays dividends	-2.17**	-2.19**	-2.17**	-2.19**	-2.17**	-2.18**
	(-2.22)	(-2.24)	(-2.23)	(-2.24)	(-2.22)	(-2.23)
PP&E/Assets	3.03	3.13	3.02	3.20	3.05	3.10
	(0.50)	(0.51)	(0.49)	(0.52)	(0.50)	(0.51)
Market leverage	28.37***	27.65***	28.35***	27.62***	28.32***	27.73***
	(6.63)	(6.46)	(6.63)	(6.45)	(6.62)	(6.47)
% Held by institutions	-0.93	-0.89	-0.90	-0.86	-0.96	-0.91
	(-0.87)	(-0.83)	(-0.84)	(-0.80)	(-0.89)	(-0.85)
Constant	58.72***	61.44***	58.29***	60.64***	58.91***	61.79***
	(6.38)	(6.62)	(6.34)	(6.55)	(6.41)	(6.67)
Observations	9,839	9,839	9,839	9,839	9,839	9,839
R-squared	0.13	0.13	0.13	0.13	0.13	0.13

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

Table 4

Tweeting Before Small and Large Surprises and Post-Announcement CARs

This table reports OLS regressions in which the dependent variable is post-announcement CAR over days [+2,+60], winsorized at the 1% level on both tails. *Ln*(*1+No. of tweets*) is the natural log of the number of tweets the firm makes over a given window around the announcement. *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 (1)-(3) restrict the sample to positive earnings surprises (earnings that beat the mean forecast), and Models (4)-(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 heteroskedasticity-robust standard errors are in parentheses.

	Dependent Variable: Size/BM Adjusted Post-Announcement CAR [+2,+60]					
	(1)	(2)	(3)	(4)	(5)	(6)
Sample:	Positive Surprises			Negative Surprises		
Tweet Window:	[-20,-2]	[-1,+1]	[+2,+30]	[-20,-2]	[-1,+1]	[+2,+30]
Ln(1+No. of tweets)	0.02	-0.24	0.09	0.29	-0.26	-0.00
	(0.10)	(-0.90)	(0.44)	(0.62)	(-0.44)	(-0.01)
Small positive surprise * Ln(1+No. of tweets)	0.56**	1.04***	0.58***			
	(2.40)	(3.26)	(2.66)			
Small negative surprise * Ln(1+No. of tweets)				-0.61	-1.00	-0.53
				(-1.25)	(-1.50)	(-1.15)
Small positive surprise	-0.43	-0.57	-0.73			
	(-0.55)	(-0.81)	(-0.89)			
Small negative surprise				1.01	1.00	1.02
				(0.58)	(0.67)	(0.57)
SUE	1.16***	1.16***	1.16***	-0.60***	-0.60***	-0.60***
	(3.12)	(3.10)	(3.11)	(-4.04)	(-4.08)	(-4.05)
Ln(Assets)	-7.36***	-7.33***	-7.38***	-9.38***	-9.14***	-9.25***
	(-5.73)	(-5.72)	(-5.76)	(-3.18)	(-3.09)	(-3.12)
M/B	-2.15***	-2.18***	-2.15***	-4.96***	-4.97***	-4.95***
	(-4.53)	(-4.58)	(-4.53)	(-4.78)	(-4.78)	(-4.76)
Cash/Assets	-2.56	-2.44	-2.65	14.49	15.03*	14.84
	(-0.68)	(-0.65)	(-0.70)	(1.60)	(1.66)	(1.64)
Firm engages in R&D	-9.07**	-9.14**	-8.97**	-2.28	-2.90	-2.61
	(-2.47)	(-2.48)	(-2.45)	(-0.37)	(-0.47)	(-0.43)
Firm pays dividends	-0.71	-0.69	-0.72	-6.18***	-6.34***	-6.22***
	(-0.58)	(-0.57)	(-0.58)	(-2.80)	(-2.88)	(-2.83)
PP&E/Assets	2.86	2.93	3.09	4.92	4.85	5.32
	(0.39)	(0.40)	(0.42)	(0.31)	(0.31)	(0.34)
Market leverage	29.02***	28.96***	29.00***	20.33**	19.63**	20.25**
	(5.48)	(5.46)	(5.47)	(2.12)	(2.06)	(2.12)
% Held by institutions	-0.71	-0.62	-0.73	1.42	1.40	1.40
	(-0.53)	(-0.47)	(-0.55)	(0.55)	(0.54)	(0.54)
Constant	66.40***	66.04***	66.54***	57.10**	52.88**	54.95**
	(5.56)	(5.53)	(5.59)	(2.44)	(2.24)	(2.32)
Observations	6,321	6,321	6,321	2,544	2,544	2,544
R-squared	0.18	0.19	0.18	0.32	0.32	0.32

Heteroskedasticity-robust t-statistics are in parentheses. All columns include quarterly and firm fixed effects.

*** p<0.01, ** p<0.05, * p<0.10

Table 5

Financial Tweeting and Announcement CARs

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. *% 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 (1)-(2) restrict the sample to positive earnings surprises (earnings that beat the mean forecast), and Models (3)-(4) restrict the sample to negative earnings surprises (earnings that fall below the mean forecast). Models (5)-(8) restrict the sample to positive earnings surprises and also divide the sample into either below- and above-median market value of equity (Models (5) and (6)) or below- and above-median analyst coverage (Models (7) and (8)). All columns include quarterly and firm fixed effects, and t-statistics from heteroskedasticity-robust standard errors are in parentheses.

	Dependent Variable: Size/BM Adjusted Announcement CAR [-1,+1]							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Type of Surprise:	Positive Surprises		Negative Surprises		Positive Surprises			
Type of Firm:	All	All	All	All	Low Mkt. Equity	High Mkt. Equity	Low Analyst Coverage	High Analyst Coverage
Tweet Window:	[-20,-2]	[-1,+1]	[-20,-2]	[-1,+1]	[-1,+1]	[-1,+1]	[-1,+1]	[-1,+1]
% Financial tweets	-0.01	0.00	-0.01	0.01	-0.02	0.01	0.00	-0.00
	(-0.45)	(0.06)	(-0.19)	(0.50)	(-0.66)	(1.23)	(0.21)	(-0.17)
Small positive surprise * (% Financial tweets)	0.05**	0.04***			0.10***	0.01	0.08***	0.01
	(2.18)	(2.72)			(2.98)	(0.64)	(2.69)	(0.93)
Small negative surprise * (% Financial tweets)			0.00	-0.01				
			(0.01)	(-0.22)				
Small positive surprise	-2.81***	-2.94***			-3.79***	-2.19***	-3.61***	-2.40***
	(-9.85)	(-9.41)			(-6.46)	(-6.04)	(-6.48)	(-6.40)
Small negative surprise			2.33***	2.31***				
			(4.09)	(3.52)				
SUE	1.25***	1.24***	-0.04	-0.07	1.24***	1.45**	1.21***	1.59***
	(4.22)	(3.81)	(-0.33)	(-0.52)	(4.04)	(2.17)	(3.32)	(2.86)
Ln(Market equity)					-1.10	-1.85		
					(-0.66)	(-1.02)		
Ln(Analyst coverage)							1.04	0.21
							(1.19)	(0.17)
Ln(Assets)	-2.85***	-3.03***	-2.91*	-3.41**	-3.13	-1.57	-5.90***	-1.67
	(-3.18)	(-3.13)	(-1.86)	(-1.97)	(-1.28)	(-0.74)	(-3.73)	(-1.25)
M/B	-1.29***	-1.25***	-1.45***	-1.56***	-0.78	-1.58**	-1.32***	-1.10***
	(-4.32)	(-4.02)	(-2.70)	(-2.69)	(-0.94)	(-2.19)	(-2.61)	(-2.75)
Cash/Assets	-1.43	-1.11	-1.21	-7.06	1.50	-5.97*	-2.33	-3.29
	(-0.59)	(-0.42)	(-0.26)	(-1.30)	(0.34)	(-1.95)	(-0.61)	(-0.90)
Firm engages in R&D	3.40	4.08	-0.64	-0.51	10.75***	2.95	10.06***	3.96
	(1.20)	(1.10)	(-0.18)	(-0.11)	(7.35)	(0.72)	(6.57)	(0.99)
Firm pays dividends	0.24	0.16	1.04	0.18	0.87	-0.23	1.04	-0.49
	(0.35)	(0.21)	(0.73)	(0.12)	(0.61)	(-0.25)	(0.80)	(-0.52)
PP&E/Assets	5.05	3.67	-7.36	-18.06**	8.93	-5.43	4.01	-1.66
	(1.03)	(0.70)	(-0.88)	(-1.98)	(0.93)	(-0.91)	(0.50)	(-0.25)
Market leverage	9.44***	7.30**	7.24	6.41	4.84	-4.42	10.12*	3.79
	(2.90)	(2.11)	(1.10)	(0.86)	(0.62)	(-0.62)	(1.87)	(0.74)
% Held by institutions	0.90	0.80	0.03	1.00	2.43	0.11	3.37*	0.04
	(0.95)	(0.78)	(0.02)	(0.61)	(1.12)	(0.10)	(1.85)	(0.03)
Constant	36.95***	38.38***	38.11**	46.68***	33.31***	53.25***	40.76***	33.90***
	(5.33)	(5.09)	(2.41)	(2.79)	(2.99)	(5.07)	(3.74)	(2.97)
Observations	5,247	4,738	2,087	1,858	1,932	2,806	1,987	2,751
R-squared	0.26	0.27	0.36	0.39	0.34	0.23	0.34	0.26

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

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) and (10)-(12) 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 heteroskedasticity-robust standard errors are in parentheses.

Dependent Variable: % Financial Tweets in given window

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Tweet Window:	[-20,-2]	[-1,+1]	[+2,+30]	[-20,-2]	[-1,+1]	[+2,+30]	[-20,-2]	[-1,+1]	[+2,+30]	[-20,-2]	[-1,+1]	[+2,+30]
Sample:	All EPS Observations			Positive Surprise			All EPS Observations			Positive Surprise		
Positive surprise	-0.04	1.25***	-0.06				-0.13	1.40***	0.01			
	(-0.19)	(3.95)	(-0.43)				(-0.53)	(3.22)	(0.03)			
Positive surprise * Abs(Accruals)							3.53	-2.25	-0.72			
							(0.69)	(-0.32)	(-0.19)			
Small positive surprise				-0.31	0.15	0.44***				-0.23	-0.22	0.08
				(-1.25)	(0.31)	(2.92)				(-0.64)	(-0.35)	(0.47)
Small positive surprise * Abs(Accruals)										-2.13	8.26	8.99**
										(-0.29)	(0.94)	(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)	-0.20	-0.38	0.34	-0.25	-2.36*	-0.50	-0.73	-0.95	-0.04	-0.40	-2.96**	-0.45
	(-0.29)	(-0.38)	(0.78)	(-0.42)	(-1.74)	(-1.21)	(-1.01)	(-0.88)	(-0.09)	(-0.63)	(-2.05)	(-0.97)
M/B	-0.10	-0.16	-0.48**	0.16	-0.50	-0.25	-0.13	-0.40	-0.48**	0.13	-0.62*	-0.35
	(-0.56)	(-0.57)	(-2.25)	(0.84)	(-1.56)	(-1.15)	(-0.62)	(-1.27)	(-2.14)	(0.60)	(-1.74)	(-1.38)
Cash/Assets	1.51	5.50**	2.09*	0.36	7.14**	0.18	3.01*	6.68***	2.52**	1.68	7.20**	0.91
	(1.00)	(2.19)	(1.91)	(0.22)	(2.11)	(0.14)	(1.94)	(2.61)	(2.22)	(1.05)	(2.17)	(0.71)
Firm engages in R&D	-1.18	2.46	0.73	0.68	0.42	0.13	-0.87	1.36	-0.24	0.80	-0.05	0.02
	(-0.88)	(0.96)	(0.99)	(0.95)	(0.44)	(0.62)	(-0.77)	(0.71)	(-0.64)	(0.99)	(-0.05)	(0.10)
Firm pays dividends	0.27	0.94	0.42	0.84*	-0.81	-0.22	0.14	0.83	0.12	0.91*	-1.06	-0.33*
	(0.49)	(0.92)	(1.33)	(1.81)	(-0.55)	(-1.54)	(0.24)	(0.72)	(0.46)	(1.77)	(-0.64)	(-1.94)
PP&E/Assets	1.33	5.58	-0.67	2.12	-0.20	-4.06	-0.47	1.32	-3.21	1.25	-5.08	-5.07
	(0.45)	(1.23)	(-0.21)	(0.61)	(-0.03)	(-1.07)	(-0.16)	(0.28)	(-1.07)	(0.36)	(-0.81)	(-1.26)
Market leverage	-1.02	0.60	-1.73	-0.78	-1.15	0.51	-0.33	0.72	-1.34	-0.91	-2.03	0.34
	(-0.36)	(0.17)	(-1.39)	(-0.21)	(-0.23)	(0.38)	(-0.11)	(0.19)	(-1.11)	(-0.23)	(-0.39)	(0.24)
% Held by institutions	0.55	0.40	0.01	-0.29	0.87	0.23	0.37	0.31	0.00	-0.47	0.89	0.35
	(0.90)	(0.41)	(0.01)	(-0.33)	(0.78)	(0.44)	(0.55)	(0.29)	(0.01)	(-0.48)	(0.74)	(0.60)
Constant	3.87	3.58	1.22	2.00	18.07*	5.37	7.89	10.35	5.06	3.01	24.50**	5.49
	(0.66)	(0.41)	(0.29)	(0.46)	(1.76)	(1.48)	(1.27)	(1.11)	(1.31)	(0.65)	(2.25)	(1.38)
Observations	8,836	7,938	9,057	5,656	5,113	5,811	8,253	7,397	8,453	5,300	4,785	5,444
R-squared	0.56	0.52	0.54	0.57	0.53	0.59	0.51	0.50	0.44	0.52	0.51	0.46

Heteroskedasticity-robust t-statistics are in parentheses. All columns include quarterly and firm fixed effects.

*** p<0.01, ** p<0.05, * p<0.10

Figure 1

Growth in Twitter Accounts

This figure plots, as of June 2009, the percent of Twitter accounts opened in each month. Data is from www.sysomos.com.

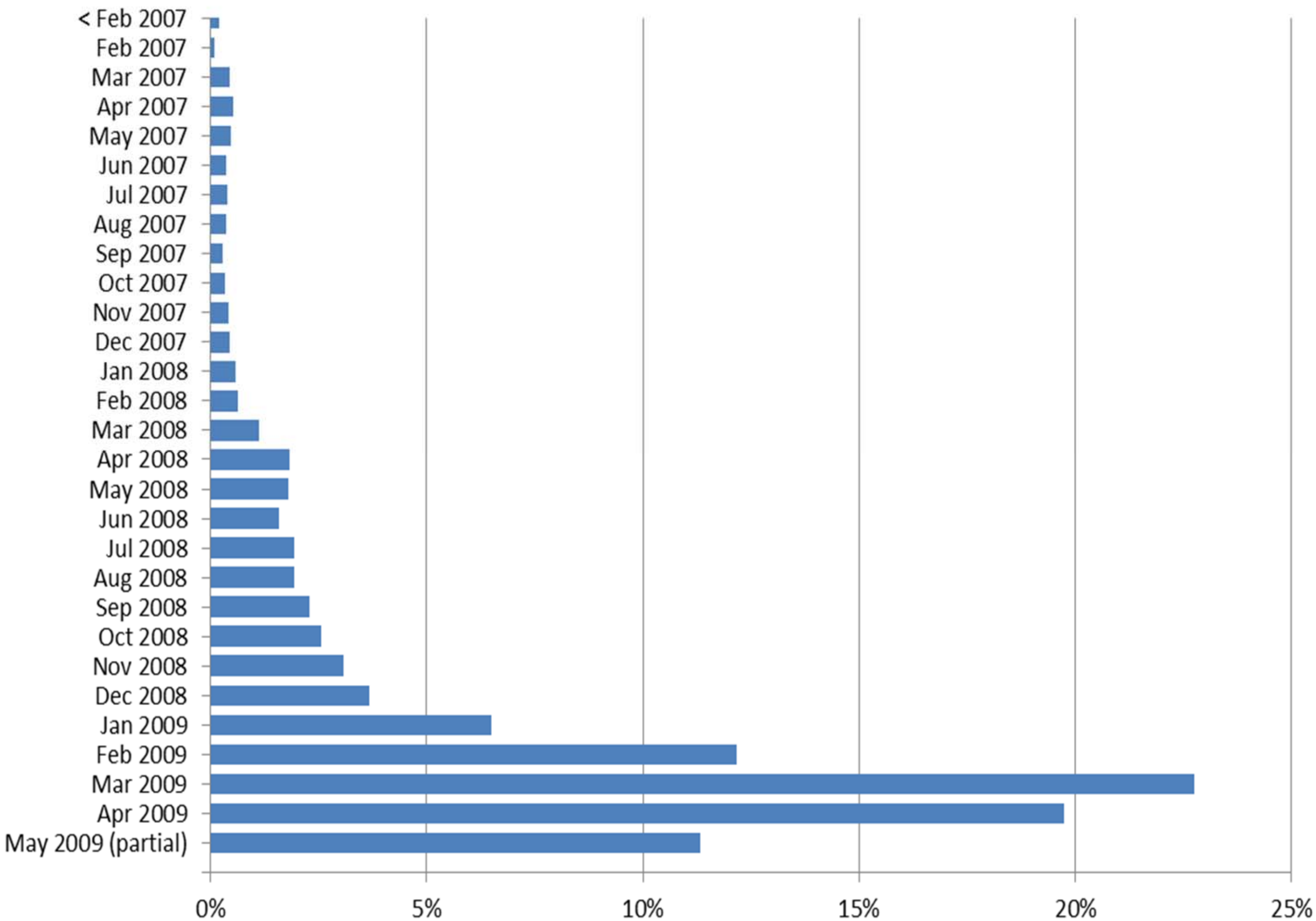

Figure 2

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).

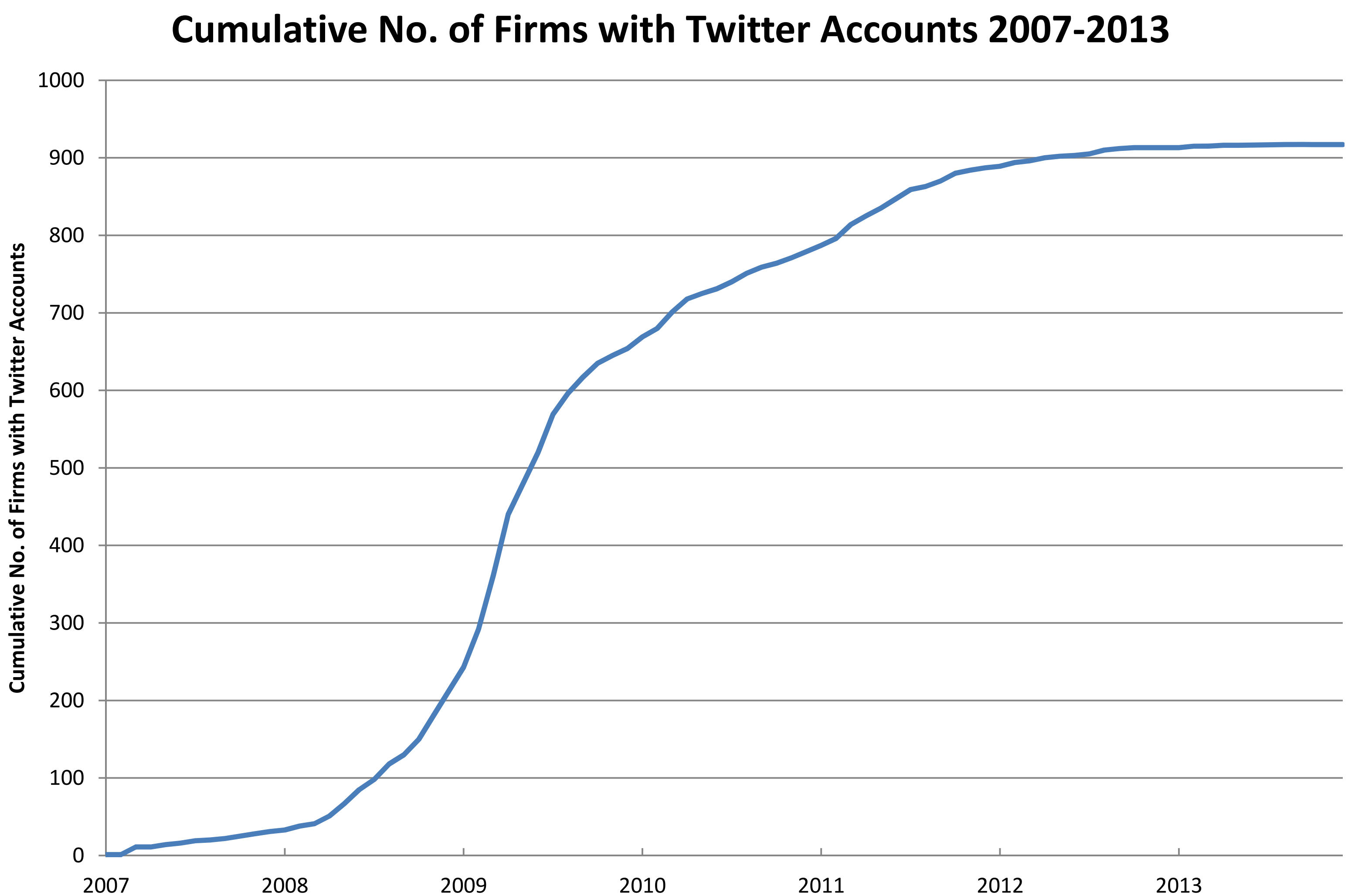

Figure 3

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).

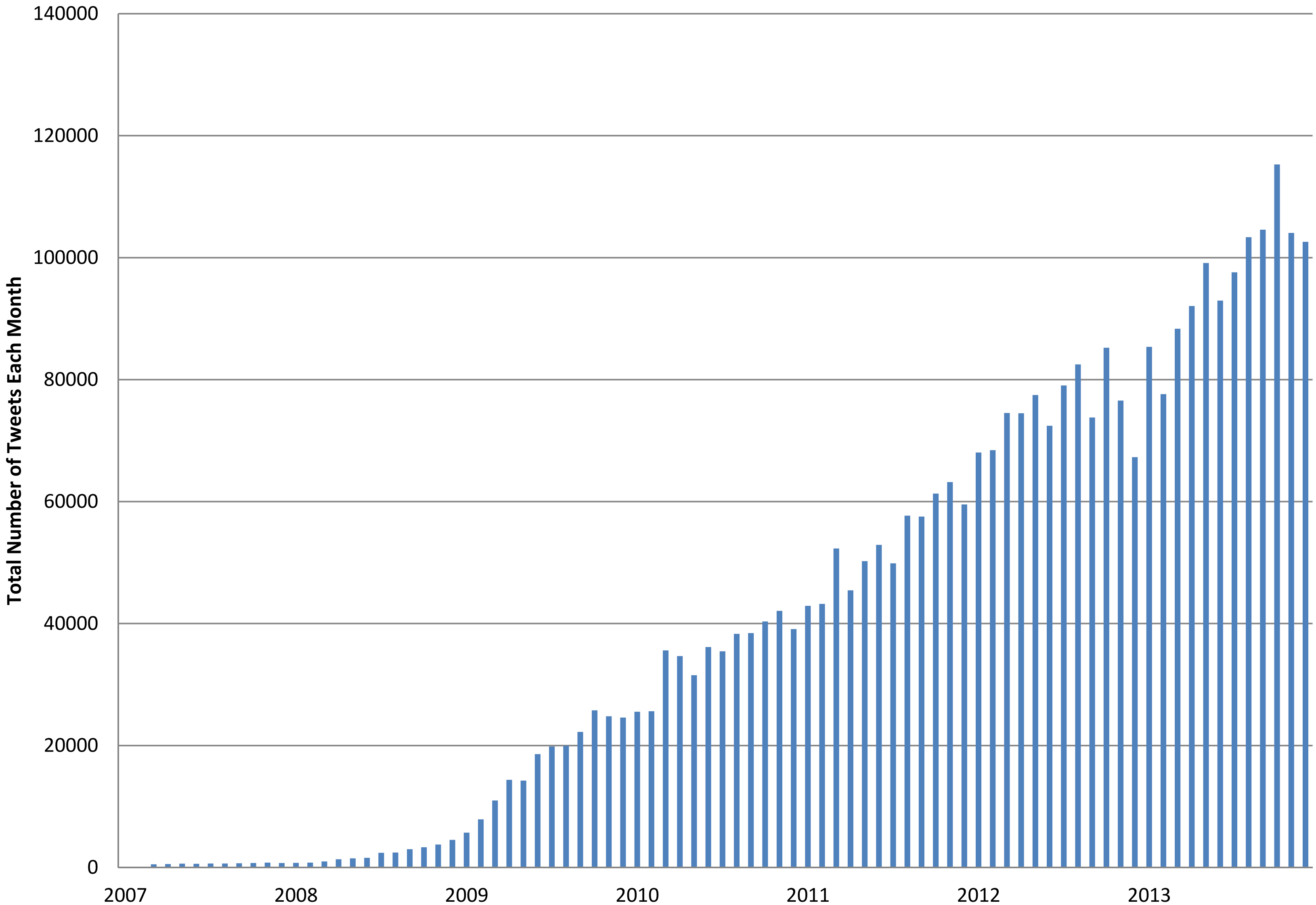

Figure 4

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).