Do Social Firms Catch the Drift?
Social Media and Earnings News

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Abstract

This paper examines whether stock price reactions to news differ based on firms' social media use. We investigate post-earnings announcement drift (PEAD) and find that Twitter-active firms have significantly stronger positive drift (and thus PEAD) following extreme positive earnings news, but also positive drift following negative news (and thus PEAD is reversed). Positive drift following negative news, which is consistent with either initial overreaction or buying during the post-announcement window, is stronger when firms tweet more often, have a larger Twitter audience, and more often tweet about their impending or just-announced earnings. These results obtain even after controlling for firm characteristics and industry fixed effects.

JEL classification: G14

Keywords: Social media; Post-earnings announcement drift; Earnings news

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Abstract

This paper examines whether stock price reactions to news differ based on firms' social media use. We investigate post-earnings announcement drift (PEAD) and find that Twitter-active firms have significantly stronger positive drift (and thus PEAD) following extreme positive earnings news, but also positive drift following negative news (and thus PEAD is reversed). Positive drift following negative news, which is consistent with either initial overreaction or buying during the post-announcement window, is stronger when firms tweet more often, have a larger Twitter audience, and more often tweet about their impending or just-announced earnings. These results obtain even after controlling for firm characteristics and industry fixed effects.

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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, co-founder 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

The internet has not only spawned a revolution in the way investors trade, thanks to online trading platforms, but also in how investors obtain information about the firms in which they invest. Many traditional sources of relevant information, such as newspapers and magazines, investment newsletters, financial services firms, and the Securities and Exchange Commission (SEC) now make their content readily available online.

More recently, the internet has dramatically altered social interaction, as the popularity of Facebook, Twitter, LinkedIn, and similar sites demonstrates. Traditional social networks appear to influence forecasts issued by analysts (Cohen, Frazzini, and Malloy 2010), trading decisions by mutual fund managers (Hong, Kubik, and Stein 2005; Cohen, Frazzini, and Malloy 2008), stock market participation (Hong, Kubik, and Stein 2004; Brown, Ivković, and Smith 2008), and trading decisions by retail investors (Shive 2010). It is thus natural to ponder whether internet-based social media, which provides firms a wide array of efficient communication methods, impacts the financial decisions of investors. In this paper we provide evidence that stock price reactions to earnings news differ based on firms' use of social media, and thus that social media offers firms a new tool with which to manage their stock price.

The most obvious firm use of social media is to connect with consumers.[1] The audience is likely to include the investment community as well, however, whether intentionally not. Some firms seem cognizant of this audience, and occasionally include social-media content that communicates strategic decisions and even information about corporate earnings. Even if a firm does not use social-media sites intentionally to communicate with investors, using social media may nonetheless impact the way investors perceive and respond to corporate news. For example, social media could help attract individual investors through familiarity, and prior research shows individual investors evaluate earnings news differently than larger investors (Battalio and Mendenhall 2005).

To investigate this issue we study stock price returns following earnings news. This setting is ideal because earnings news is material and relatively frequent. In addition, prior research provides baseline results and thus a context within which to interpret our findings. Specifically, many studies document that stock prices experience post-earnings announcement drift (PEAD), in which prices drift in the direction of the earnings news during the next few months (e.g., Bernard and Thomas 1989 and 1990). The literature interprets this finding as evidence that investors underreact when the earnings are announced, and Fama (1998, pg. 286) characterizes PEAD as the "granddaddy of underreaction events."

How a firm's use of social media should affect post-earnings announcement returns is far from clear. Social media provides firms with a low cost way to communicate directly with a broad audience, and hence could reduce underreaction to earnings news by lowering information acquisition costs (Grossman and Stiglitz 1980, Ball 1992). It could also reduce

[1] "@McDonalds Twitter Team" had eight employees listed on McDonald's web site as of December 2013, and the bios for these employees included quotes emphasizing customers in each "Twitter-sized job description."

underreaction by making news more conspicuous, thus mitigating the effects of investors' limited attention. Klibanoff, Lamont, and Wizman (1998) find that underreaction to (non-earnings) news relevant for closed-end funds is less severe when the news is more "attention-grabbing" because it appears on the front page of *The New York Times*, and Hirshleifer, Lim, and Teoh (2009) find that underreaction to corporate earnings news is less severe when it is announced on days with fewer earnings announcements by other firms. Even if a firm's social media content does not specifically refer to its earnings news, it may work to increase investor attention more generally and hence reduce underreaction.[2] The finding in Hirshleifer, Lim, and Teoh could predict that social media exacerbates underreaction, however, if firms are so indiscriminate in their social media use that investors become overly distracted by immaterial information.

Yet another potential mechanism relates to the firm-selected nature and frequency of the firm's social media activity. For example, a firm could alter the frequency of its social media use in order to influence investor attention both before and after the release of earnings results. Finally, social media could facilitate herding, and even informational cascades, due to the sequential way in which content (including that by the public) is posted (Bikhchandani, Hirshleifer, and Welch 1992, Hirshleifer and Teoh 2003).[3] Depending on the severity and direction of the herding or cascade behavior and the direction of the earnings news, this may work to either exacerbate or mitigate underreaction, or even to cause overreaction.

To conduct our study, we examine post-announcement returns over trading days +2 through +60 following earnings announcements for a sample of 4,489 publicly-traded firms

[2]For example, if social media helps investors to keep a firm forefront in their minds, these "tuned in" investors may pay greater attention to news from other sources and even seek such news out.

[3]Providing anecdotal evidence that social media can affect stock prices along these lines, the article "RPT-Twitter, social media are fertile ground for stock hoaxes" discuses short-seller impersonators using Twitter to manipulate stock prices by fraudulently tweeting short positions (http://www.reuters.com/article/2013/03/11/usa-stocks-twitter-idUSL1N0C0KQY20130311 pulled, November 14, 2013). Heimer and Simon (2013) investigate the role of a Facebook-style social network in propagating investment strategies in the foreign exchange markets.

over the 2004–2011 period. We begin by replicating the PEAD results of earlier literature with our updated sample, and like others find that PEAD is less pervasive in recent years (e.g., Huang, Nekrasov, and Teoh 2012). Our measure of a firm's social media use is based on Twitter. This choice is motivated by the site's popularity, its promotion to firms for business use,[4] and the ability to derive firm-specific measures of the intensity of a firm's social media use and the audience size by recording the number of tweets the firm makes and the number of twitter users that "follow" the firm's tweets.[5]

We divide our sample into "Twitter firms" and "non-Twitter firms," where Twitter firms are required to have at least a modest number of tweets and followers,[6] and separately examine three time periods based on milestones in Twitter's creation and rise in popularity: a pre-Twitter period (1/1/2004–3/31/2006), an early-Twitter period (4/1/2006–12/31/2008), and a mature-Twitter period (1/1/2009–12/31/2011). We use the pre-Twitter period as a placebo period by coding EPS announcements during this time period as originating from a Twitter or non-Twitter firm based on whether the firm later became active on Twitter.

We find that both Twitter and non-Twitter firms have significant and fairly similar PEAD during the pre-Twitter period. Differences begin to emerge in the early-Twitter period, and in the mature-Twitter period differences are striking: Non-Twitter firms experience insignificant returns following extreme positive earnings news and weak PEAD following extreme negative earnings news. Twitter firms, however, experience significant, positive returns (PEAD) following extreme positive earnings news. Moreover, and more noteworthy,

[4]Twitter actively promotes itself for business purposes, noting that it "offers businesses an easy way to reach an engaged audience" and that "businesses use Twitter to quickly share information with people interested in their products and services, gather real-time market intelligence and feedback, and build relationships with customers, partners and influencers" (quoted from the site on March 28, 2013).

[5]Blankespoor, Miller, and White (2013) examine the use of Twitter by a sample of technology firms and find that a firm's use of Twitter increases the liquidity of the firm's stock, consistent with a reduction in information asymmetry.

[6]For example, a firm with only four lifetime tweets and a handful of followers is coded as a non-Twitter firm because it does not use Twitter in a meaningful way. Some firms, for example, appear to create accounts as placeholders for potential future use.

they also experience significant, positive returns following extreme *negative* earnings news. Thus, for Twitter firms in the mature-Twitter period, there is stronger PEAD following extreme positive earnings news, and a post-earnings announcement *reversal* (PEAR) following extreme negative earnings news. We are not the first to document PEAR for a subset of earnings announcements, as Huang, Nekrasov, and Teoh (2012) find PEAR when positive earnings-news press release headlines are made more salient by including a greater amount of hard numbers.

A firm's decision to use Twitter is clearly not exogenous. Therefore, despite similar univariate PEAD results for Twitter and non-Twitter firms during the placebo, pre-Twitter period, the rest of our analysis provides further evidence on the extent to which differences in post-announcement returns are due to self-selection (differences in the types of firms that choose to use Twitter) versus the use of Twitter itself.[7] We begin by controlling for a multitude of firm characteristics in cross-sectional regressions that explain post-announcement returns following extreme negative EPS announcements (Q1 $\equiv$ quintile 1), and separately for returns following extreme positive announcements (Q5 $\equiv$ quintile 5). Regressions show that in both the placebo, pre-Twitter period and early-Twitter period, there are no significant differences in the post-announcement returns between firms we classify as Twitter and non-Twitter firms. In the mature-Twitter period, however, post-announcement returns are higher for Twitter firms following both Q1 and Q5 announcements.

To further mitigate the selection bias in which firms choose to be active on Twitter and to learn whether the *nature* of a firm's Twitter use maters, we perform additional analysis on only Twitter firms during the mature-Twitter period. Regressions show that for Q1 (but not Q5) announcements, post-announcement returns are significantly higher for firms with

[7]For example, firms with a large retail consumer base (McDonald's, Best Buy, etc.) are likely to be active on social media for product-market reasons, and retail investors may be gravitate to such firms because they are familiar or attract their attention (Barber and Odean 2008). If retail investors respond differently to earnings news than non-retail investors and have the ability to move prices, they could cause post-earnings returns to differ between Twitter and non-Twitter firms.

higher tweeting intensity (those that tweet more often), and for those that have a larger Twitter audience (i.e., a greater number of Twitter "followers").

Further analysis shows that in the case of negative earnings news (Q1), the actual content of a firm's tweets matters significantly. We count the number of each firm's tweets that specifically refer to earnings (whether impending or just announced) during the period beginning 45 calendar days before the earnings are announced and ending one day after. For negative (but not positive) earnings news, more frequent tweeting about earnings during calendar days [-45,+1] is associated with higher post-announcement returns even after controlling for firm characteristics, industry fixed effects, general tweeting intensity, and Twitter audience size. Moreover, the marginal effect of tweeting about earnings is larger when the firm's Twitter audience is larger. These results provides important evidence consistent with the notion that the use itself of Twitter matters, at least for negative earnings news.

We also investigate the effect of tweeting about earnings during the post-announcement return window. For negative (but not positive) earnings news, tweeting more often about earnings during days [+2, +45] is associated with significantly higher post-announcement returns, and once again this result obtains even after controlling for firm characteristics, industry fixed effects, general tweeting intensity, and Twitter audience size. There are two ways to interpret this result. First, recall that the average Q1 (negative) earnings announcement by Twitter firms is followed by PEAR, or post-earnings announcement reversal as manifested by a positive drift. In the framework of how prior literature interprets drift in the same direction of earnings news as evidence of underreaction, this drift in the *opposite* direction is consistent with an *overreaction* followed by a correction (as in Huang, Nekrasov, and Teoh 2012). It is possible that firms correctly perceive there has been an overreaction to their negative earnings news, and that they more actively tweet about earnings during the post-announcement window in a manner that positively influences investor trading.

A subtly different possibility is that some firms are more active than others in guiding how their Twitter audience reacts to negative earnings news, and that they successfully influence investors to *believe* (perhaps *incorrectly*) that the market has overreacted. Here too, investors would perceive a buying opportunity and their trading could influence prices higher. Indeed, Hirshleifer, Myers, Myers, and Teoh (2008) examine transaction data and find that retail investors are net buyers after both good and bad extreme earnings news. Additionally, as Barber and Odean (2008) show that retail investors are more likely to buy than to sell "attention-grabbing stocks," increasing retail-investor awareness of the firm by tweeting about negative earnings could, counterintuitively, push prices higher.[8,9]

Overall, our findings imply that a firm's social media audience includes investors, even if the content it posts is not aimed at the financial community specifically, and that social media impacts the way in which stock prices respond to earnings news. This impact is more pronounced for firms with a larger social media following, and also differs based on the direction of news and the nature of the firm's social media use. More genenerally, our findings indicate that firms can use social media to manage their stock prices. In light of the SEC's April 2013 approval of social media to comply with the disclosure requirements of Regulation Fair Disclosure ("Reg FD"), the use of social media to communicate with investors is likely to grow. Therefore, we argue the SEC should monitor closely the evolution of corporate use of social media and its impact on stock prices.

[8]This would be in line with the adage used in certain settings that "there is no such thing as bad news." A Twitter-related example is the finding in DiGrazia, McKelvey, Bollen, and Rojas (2013), in which political candidates receive more votes when their names are mentioned more often in tweets, whether complimentary or not.

[9]For this channel to help explain our findings, trading by retail investors would have to move prices. Papers showing that correlated retail trading affects security prices include Kumar and Lee (2006), Barber and Odean (2008), Hvidkjaer (2008), and Barber, Odean, and Zhu (2009).

2. Data

We begin with active publicly-traded firms in the Center for Research in Security Prices (CRSP) database at the end of 2011 (we exclude closed-end funds, real-estate investment trusts, limited partnerships, and American depository receipts).[10] 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 2011. 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.[11] 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.

To construct data on each firm's Twitter presence, during March 2012 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 the Twitter account (if one is listed) 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.

As we do not have a machine-readable historical record of all tweets, we measure the intensity of a firm's Twitter use on an ex post basis as the average intensity over the lifetime

[10] We do not attempt to include firms that went bankrupt or otherwise ceased to exist before the end of 2011, because the ex post data we observe on Twitter to measure the intensity of Twitter use would be misleading for such defunct firms. For example, a defunct firm that did not close its Twitter account could appear to be a very infrequent user of Twitter with few followers, even though the opposite may have been true while the firm was viable.

[11] 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.

of its Twitter use.[12] To define each firm's *Tweet intensity* we calculate the ratio of (a) the number of tweets between the account's creation (which at its earliest in our sample is during November 2006) and December 1, 2012 to (b) the number of days between the account's creation and December 1, 2012. *Tweet intensity* is set to zero for all firms whose accounts were established in January 2012 or later, because we only study EPS announcements made prior to 2012.

Many firms have multiple Twitter accounts, so when constructing *Tweet Intensity* we aggregate data to construct one observation per firm by summing the number of tweets across accounts for the numerator, and using the number of days since the earliest account was created for the denominator. We then define an indicator variable *Twitter Firm*, which is set to one if the firm both has at least one Twitter account and *Tweet Intensity* exceeds 0.10 (i.e., the firm has tweeted, on average, more than one tweet every 10 days since creation of its earliest Twitter account). Our motivation for not defining a firm's Twitter status simply based on whether it has an account is that an inspection of tweeting activity makes it clear that some firms simply create accounts as placeholders for future use, or to prevent a particular Twitter "handle" (i.e., account name) from being created and used by other parties. The choice of 0.10 as the cutoff results from a casual inspection of the distribution of *Tweet Intensity*, and inferences are robust to varying this cutoff or defining *Twitter Firm* based on the number of followers (which, as we report later, is strongly correlated with *Twitter Intensity*). Our sample contains 670 tweeting firms (those with *Twitter Firm* = 1) and 3,819 non-tweeting firms (those with *Twitter Firm* = 0).

Quarterly earnings announcement dates are from the I/B/E/S database during the years 2004-2011. For each EPS announcement, from CRSP we obtain returns from +2 to +60

[12] Time-series variation in the intensity of a firm's Twitter use will add noise, but should not bias our analysis. To test this claim, in unreported analysis we take advantage of the fact that such noise will be more severe, on average, for firms who have had active accounts for longer periods of time. We do not find qualitatively different results for firms that opened their accounts more recently compared to those with longer-lived accounts.

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). Our measure of post-announcement returns is the cumulative abnormal return over these days, which is the sum of daily abnormal returns where an abnormal return is the firm's return minus the equally-weighted CRSP return including dividends. We choose the equally-weighted CRSP return to more fairly represent a firm chosen at random, given that our sample population is not skewed toward large firms (we report robustness results using the value-weighted CRSP return). The final sample contains 76,147 EPS observations.

Our analysis divides the sample into three time periods: a pre-Twitter period (2004 through March 2006, when Twitter was created), an early-Twitter period (April 2006–2008), and a mature-Twitter period (2009–2011) in which Twitter gained significant popularity. Although Twitter was created in 2006, the year 2009 marked a major increase in usage. 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. Growth in Twitter accounts is plotted in Figure 1.

Although our main focus is on the mature-Twitter period, we include some initial results for the early-Twitter period to show the transition that took place as Twitter initially grew. We also report some results on the pre-Twitter period as a placebo analysis that helps identify the extent to which differences in post-announcement returns between Twitter and non-Twitter firms during the mature-Twitter period are merely due to differences in the types of firms that later chose to become active on Twitter. To implement the placebo analysis, we classify EPS observations in the pre-Twitter period as belonging to a Twitter or non-Twitter firm on the basis of whether the firm *eventually* became a Twitter firm during the early- or mature-Twitter periods. This allows us to examine whether post-earnings announcement returns differ before Twitter even existed between firms that did and did not later become active on Twitter. For the early- and mature-Twitter periods, we classify EPS observations as belonging to a Twitter or non-Twitter firm jointly based on whether *Tweet Intensity* exceeds 0.10 and whether the firm's account opened before the EPS announcement date.[13]

Table 1 reports summary statistics for firm characteristics, grouped by Twitter and non-Twitter firms. Given that the sample spans eight years and that we analyze three distinct time periods, we tabulate these statistics using the latest available data as of the beginning of 2004, 2008, and 2011. Sample sizes grow over time due to not all firms being active (with data on CRSP, Compustat, and I/B/E/S) by 2004. Firms are classified as Twitter or non-Twitter for the 2004 statistics as described above for EPS observations in the pre-Twitter period, and similarly as described above for the early- and mature-Twitter periods for the 2008 and 2011 statistics, respectively.

On average, Twitter firms seem to be larger in terms of book assets, have higher market-to-book (M/B) ratios, have more cash as a percentage of book assets, are more likely to engage in research and development (R&D), are less likely to pay dividends, have lower leverage ratios and ratios of property, plant, and equipment plus inventories (PP&E + Inv) to assets, and have more of their shares held in large blocks by institutions.[14] These differences seem apparent at all three measurement points. Thus, if differences in firm characteristics between Twitter and non-Twitter firms drive any significant observed differences in PEAD, presumably such differences would be observed in all three of the time periods we examine.

[13]For example, consider a firm with *Tweet Intensity* exceeding 0.10 that opened its Twitter account during January 2007 with earnings announcements each February, May, August, and November. All EPS announcements during the pre-Twitter period (2004-March 2006) would be classified as a belonging to a Twitter firm to implement the placebo treatment. For the early-Twitter period (April 2006-2008), EPS announcements made May 2006, August 2006, and November 2006 would be classified as a non-Twitter-firm EPS announcements because they occurred prior to the account opening in January 2007. EPS announcements occurring February 2007 and later would be classified as Twitter-firm EPS announcements in both the rest of the early- and mature-Twitter periods.

[14]We define market-to-book (*M/B*) as the book value of debt plus the market value of equity all divided by the book value of assets, *Leverage* as long-term debt plus current liabilities all divided by book assets, and *Institutional Block Ownership* as the percent of shares collectively owned by institutions that own at least 5% of the firm's stock.

We do not attempt to discern the statistical significance of differences in firm characteristics, however, because our goal is simply to motivate the potential need to control for firm characteristics in our later analysis.

3. Univariate Post-Announcement Return Results

In Table 2 we document post-earnings announcement returns for the three time periods and the five quintiles of earnings surprises, where an earnings surprise is defined as the deviation of the EPS realization from the median analyst forecast, all scaled by the stock price one week prior to the earnings announcement. Quintiles are defined monthly based on all EPS announcements in the month.

The first column of numbers reports average post-announcement returns for all EPS observations during the placebo, pre-Twitter period (2004-2006Q1). The average post-announcement return for the lowest announcement-return quintile (Q1) is negative (-1.28%) and statistically significant, while that for the highest announcement-return quintile (Q5) is positive (1.38%) and statistically significant. Thus, we find significant PEAD for the extreme earnings quintiles, and the difference between Q5 and Q1 (2.66%) is statistically significant with a t-statistic of 8.03.

The second column of numbers indicates that the difference between post-announcement returns for Q5 and Q1 (2.22%) is somewhat less pronounced in the early-Twitter period (2006Q2-2008) than the 2.66% difference in the placebo, pre-Twitter period. The mature Twitter period (2009-2011) displays yet less pronounced PEAD, and the average post-announcement return for Q1 is not statistically different from zero. Other studies also find that overall, PEAD is less pronounced in later time periods (e.g., Huang, Nekrasov, and Teoh 2012).

The last six columns report post-announcement returns for each period, separately for non-Twitter- and Twitter-firm EPS observations (based on *Twitter Firm* as defined earlier). During the placebo, pre-Twitter period, Q1 observations exhibit similar levels of PEAD (negative drift following negative earnings surprises) for both non-Twitter and Twitter-firm EPS observations of -1.31% and -1.10%, respectively. For Q5 observations, the magnitude of PEAD is somewhat larger for Twitter-firm EPS announcements, but later we show this result does not hold after controlling for firm characteristics. For the early-Twitter period, non-Twitter-firm EPS announcements experience significant PEAD in both Q1 and Q5 quintiles, and the difference between Q5 and Q1 (2.24%) is statistically with a t-statistic of 5.51. Twitter-firm EPS announcements do not exhibit PEAD in the early-Twitter period: Q1 announcements have small *positive* post-announcement returns of 0.72%, and Q5 announcements have post-announcement returns that are not statistically significant.

Differences between Twitter- and non-Twitter EPS announcements are most pronounced during the mature-Twitter period. For extreme positive earnings news (Q5), only Twitter EPS announcements display significant PEAD, and the difference in post-announcement returns between Twitter and non-Twitter EPS observations larger in magnitude than in the other two periods. The most striking difference is for extreme negative earnings news (Q1): non-Twitter EPS announcements experience weak-magnitude PEAD with an average return of -0.50%, while Twitter EPS announcements experience a large PEAR (post-earnings announcement *reversal*) of 2.05%.

Given that the literature interprets PEAD as evidence that investors underreact to earnings news, the analogous interpretation in the case of PEAR for Twitter-firm EPS announcements in the mature-Twitter period is that investors *overreact* to extreme negative earnings news. In a study of EPS press release headlines, Huang, Nekrasov, and Teoh (2012) find PEAR for a subset of earnings news and also interpret this result as evidence of overreaction. An alternative possibility, however, is that some investors believe (perhaps incorrectly) that the market overreacted to the negative earnings news, and that the buying opportunity they perceive results in buying activity that pushes prices higher. Hirshleifer, Myers, Myers, and Teoh (2008) document that retail traders are net buyers after both good *and bad* earnings news, and that buying intensity is stronger following larger earnings surprises.

4. Firm Characteristics or Social Media Use?

4.1. Motivation

There are two obvious possibilities for why post-announcement returns differ between Twitter-firm and non-Twitter-firm EPS announcements. The first is that, as discussed in the introduction, social media use itself affects how investors respond to earnings news. For example, social media could help investors stay informed about firm news and mitigate limited attention, distract investors and *exacerbate* limited attention, facilitate herding behavior, etc. We use "social-media channel" to denote the overarching possibility that the use of social media itself affects post-EPS announcement returns.

The second possibility is that there could be something different about firms that use Twitter that causes investors to interpret earnings news differently. For example, firms that are very different in their underlying characteristics could also have investor clienteles that differ in how they respond to earnings news. We use "self-selection channel" to denote the possibility that post-earnings returns are different for Twitter firms due to differences in firm characteristics.

These two channels are unlikely to be mutually exclusive, and both have important implications. The self-selection channel highlights the importance of firm characteristics in understanding cross-sectional differences in how stock returns respond to news. The social-media channel implies that firms could use social media strategically to manage investor reaction to news, as well as to manage their stock prices more generally.

The rest of our analysis aims to better understand the extent to which one or both of these channels explain differences in post-announcement returns between Twitter- and non-Twitter-firm EPS announcements in the mature-Twitter period. The univariate results in Table 2 suggest that the self-selection channel is not the only one at play because differences between returns for Twitter- and non-Twitter EPS announcements are more pronounced in the mature-Twitter period than in the placebo, pre-Twitter period. However, regression analysis can shed further light.

4.2. Multivariate Regressions of Post-Announcement Returns

Models (1) and (2) of Table 3 report regressions that explain post-EPS announcement returns for Q1 and Q5 announcements, respectively, in the placebo, pre-Twitter period. We include a wide variety of control variables in addition to the main variable of interest, *Became Twitter Firm*, which is an indicator set to one for EPS announcements made by firms that later became Twitter firms. The coefficient for *Became Twitter Firm* is insignificant in both regressions, showing that after controlling for firm characteristics, in the pre-Twitter period there are no statistically significant differences in post-announcement returns between firms that later became active on Twitter and those that did not.

As noted earlier, during the early-Twitter period the indicator *Twitter Firm* is set to one based on whether the EPS announcement is by a firm with *Tweet Intensity* of at least 0.10 and with an account creation date before the EPS announcement. Here too there is no significant difference between Twitter and non-Twitter EPS post-announcement returns, as the insignificance of *Twitter Firm* indicates. This is not overly surprising given that Twitter was in its early years and had not yet achieved popularity in terms of accounts and audience.

The mature-Twitter period regressions, however, show that returns are significantly higher following Twitter-firm EPS announcements. The coefficients on *Twitter Firm* in models (5) and (6) indicate that after controlling for firm characteristics, the average Q1 EPS announcement by a Twitter firm experiences a post-announcement return that is 1.46% higher ($t = 1.99$) than that by a non-Twitter firm, and similarly the average Q5 announcement return is 1.84% higher ($t = 3.21$).

Beginning in Table 4 the analysis focuses exclusively on the mature-Twitter period in which there are stark differences in Twitter and non-Twitter post-earnings announcement returns.[15] In Table 4 we repeat the specifications in Table 3, but depending on the model, include Fama French-49 industry fixed effects and also *Advertising/Sales.* The motivation for including industry fixed effects is to further control for firm characteristics that are shared across firms in similar industry groups that might jointly increase the likelihood of being active on Twitter and affect the way investors interpret earnings news. Arguably, including industry fixed effects unfairly stacks the deck against the social-media channel. If the social-media channel is operative, it is likely to be much more so in some industries than others, so that including industry fixed effects will make it very difficult to detect. Nevertheless, we include industry fixed effects to set a high bar in detecting the social-media channel by further controlling for the self-selection channel.

The motivation for *Advertising/Sales* is that firms that rely heavily on advertising to generate sales are more likely to have a broad retail customer base, which also makes them more likely to participate in social media, and separately, to attract retail investors who possibly respond differently to earnings news than non-retail investors. Thus, including this variable has the same potential advantage and disadvantage as including industry fixed

[15] In untabulated results we estimate the regressions in Table 4 on the pre-Twitter placebo period. The coefficients on *Twitter Firm* for the Q1 announcements (models 1-3) are insignificant. *Twitter Firm* is significant at the 10% level in model (5) for Q5 announcements, but is insigificant in models (4) and (6) which include industry fixed effects.

effects. An additional and severe disadvantage, however, is that this variable is missing for more than half of the firms in our sample, and hence including it significantly reduces statistical power.

Models (1)-(3) show that Q1 (negative surprise) EPS announcements by Twitter firms do not have significantly higher post-announcement returns after including industry fixed effects and *Advertising/Sales*. In contrast, models (4)-(6) for Q5 (positive surprise announcements) show that *Twitter Firm* continues to be economically and statistically significant, with coefficients ranging from 2.02 to 2.57 and t-values ranging from 2.77 to 3.15. Thus, based on Table 4 alone, there is stronger support for the social-media channel in positive earnings surprises than in negative earnings surprises.

In Tables 5 and 6 we alter the analysis in two ways to further investigate the social-media channel. First, we at least mitigates the self-selection channel by only including Twitter-firm EPS observations (i.e., non-Twitter-firm EPS observations are excluded). Second, this analysis introduces new variables that measure how Twitter is used, as well as its reach. For Table 5, these variables are *Tweet Intensity* and *Twitter Followers*. *Tweet Intensity* was defined earlier, and is the average number of tweets the firm makes over the lifetime of its account. *Twitter Followers* is simply the number of Twitter users as of December 1, 2012 (when *Tweet Intensity* is measured). Given the earlier results, the social-media channel predicts these regressors to positively correlate with post-announcement returns.[16] We use log-transformations for both variables to mitigate concerns about skewness and outliers. The regressions include industry fixed effects, but not *Advertising/Sales* because this variable is never significant and we wish to preserve sample size.

[16] Although *Tweet Intensity* is clearly not exogenous, it provides helpful evidence because of its clear, directional prediction of positive correlation with post-announcement returns under the social-media channel (given the earlier results of higher Twitter-firm post-announcement returns). Note that *No. of Twitter Followers* has the same directional prediction, and after controlling for *Tweet Intensity* and firm characteristics, is much less of a choice variable for the firm. Finding that neither of these variables positively correlate with post-announcement returns (given earlier results) would cast doubt on the social-media channel.

Models (1)-(4) focus on negative earnings surprises (Q1). Model (1) shows that post-announcement returns positively correlate with *Tweet Intensity*, although the statistical significance is weak ($t = 1.69$). The coefficient of 1.24 implies that an increase of one standard deviation (SD) in *Ln(Tweet Intensity)* is associated with an absolute increase in post-announcement returns of 1.63%. In model (2), the significant coefficient on *Ln(No. of Twitter Followers)* of 1.34 implies that a one-SD increase in *Ln(No. of Twitter Followers)* is associated with an absolute increase in post-announcement returns of 2.87%. Model (3) suggests that *Twitter Followers* remains significant after controlling for the frequency of the firm's Twitter use, and also has more explanatory power than *Tweet Intensity.*[17]

Models (5)-(8) repeat the regressions for positive earnings surprises (Q5), and none of the key variables are significant. This insignificance does not necessarily rule out the social-media channel as playing a role in Q5 announcements, given the earlier results. It does, however, suggest that the *nature* of the firm's Twitter use does not impact post-announcement returns following extreme positive earnings news, and at least makes the case for the social-media channel more tenuous.

In Table 6 we focus on the content of the firm's tweets. Specifically, we inspect the firm's tweets surrounding its EPS announcement and hand count the number of tweets in which the firm refers to its impending or just-announced earnings.[18] We only report results for negative earnings surprises (Q1), because we do not find any significant results for positive earnings surprises (Q5). Similar to Table 5, the lack of significance for Q5 suggests that the nature of the firm's Twitter use is not a significant factor in explaining cross-sectional differences in

[17] We note that although *Tweet Intensity* and *No. of Twitter Followers* are positively correlated as expected, the correlation of $\rho = 0.67$ and the variance inflation factors in our main regression model of 2.21 and 2.80, respectively, suggest there are not extreme multicollinearity concerns.

[18] Casual inspection shows that the nature of such tweets varies. Those timed before the earnings release usually alert followers to the impending announcement and how they can listen to the earnings call. Those timed after the release may direct users how to listen to a replay, or they may "retweet" the tweets of others who have commented on the earnings release, or refer users to articles about the earnings or discussion by firm executives, or respond directly to other users who have commented on the earnings.

post-announcement returns following extreme positive earnings announcements by Twitter firms. To mitigate concerns over skewness and the effect of outliers, we take the natural log of one plus the number of earnings tweets (we add one because the lower bound is zero).

In panel A we count such tweets over calendar days -45 to +1 relative to the EPS announcement date. The motivation is that by calling attention to its impending or just-announced earning release, the firm may impact the way investors react to earnings (for example by increasing the attention of investors and making the earnings news more salient). Of the 639 EPS observations in the regression's sample, 188 have at least one tweet during days -45 to +1 that contain the word earnings. Models (1)-(4) show that a greater number of earnings tweets results in more positive post-announcement returns, even after controlling for the firm's propensity to tweet more generally (*Tweet Intensity*) and Twitter audience size (*No. of Followers*). The coefficients imply that for a one-SD increase in *Ln(No. of Earnings Tweets)*, post-announcement returns are higher by an absolute 1.22% to 1.49% depending on the model.

Model (5) shows there is an intuitive interactive effect between earnings tweets and the number of Twitter users following the firm's tweets. The model implies that if both *Ln(No. of Earnings Tweets)* and *Ln(No. of Followers)* increase by one SD, the post-announcement return is higher by an absolute 6.19%. Additionally, if we hold *Ln(No. of Followers)* at its sample mean, a one-SD increase in *Ln(No. of Earnings Tweets)* is associated with a 1.8% increase in post-announcement returns, but if *Ln(No. of Followers)* is one SD above than its sample mean, a one-SD increase in *Ln(No. of Earnings Tweets)* is associated with a 3.07% increase in post-announcement returns. Thus, the marginal effect of a greater number of earnings tweets is much more pronounced when there are more followers, which is an intuitive result under the social-media channel.

In model (6), we show that the positive correlation between post-announcement returns and *Ln(No. of Earnings Tweets)* is robust to controlling for both *Ln(Tweet Intensity)* and *Ln(No. of Followers).* Model (7) shows that the interaction effect between *Ln(No. of Earnings Tweets)* and *Ln(No. of Followers)* survives including *Ln(Tweet Intensity)* as an additional control variable. As a final check that tweeting about earnings matters after controlling for tweeting intensity and audience size, model (8) includes the first principal component of both and shows that the magnitude and statistical significance of coefficient on *Ln(No. of Earnings Tweets)* is qualitatively similar to the earlier models without interaction terms.

It is worth noting that the marginal effect of *Ln(No. of Earnings Tweets)*, which is most readily observable in the six models without interaction terms, is relatively stable regardless of the Twitter-related control variables included. It is also worth noting that firms with particularly high degrees of tweeting intensity in general (high *Tweet Intensity*) are not necessarily more likely to tweet more often about earnings—the correlation between *Ln(Tweet Intensity)* and *Ln(No. of Earnings Tweets)* is only 0.013. Thus, for Twitter-active firms, the policy choice of general tweeting intensity seems distinct from its choice of how often to tweet about earnings.

In panel B, earnings tweets are counted during calendar days +2 to +45. Here, the idea is that firms may use Twitter to manage the way investors interpret earnings results. In the case of negative earnings news, they may communicate measures they are taking to improve future results, or imply that the latest news is merely transitory and not reflective of the firm's expected future performance. Models (1)-(4) show that post-announcement returns are positively associated with earnings tweets, with the marginal effect of a one-SD increase in the number of such tweets ranging from an absolute 0.68% to 0.90%. Model (5) implies there is not a significant interaction effect with the number of followers, and models (6) and (7) show the results in models (4) and (5) are robust to controlling for *Tweet Intensity.*

Model (8) shows the marginal effect of tweeting about earnings is qualitatively unchanged when controlling for the first principal component of tweeting intensity and audience size.

4.3. Robustness

In this section we include two sets of robustness checks for the results in Tables 4 through 6. Panels A through D repeat the specifications in Table 4, Table 5, and Table 6 panels A and B, but include *EPS Announcement Return* (the CAR over days -2 to +1) as an additional regressor. By including the announcement return, we mitigate the concern that the post-announcement return results are due to starting the post-announcement window too soon. Although the specifications are the same as in the tables except for this additional variable, for brevity we only report the key variables of interest. Panel A shows that the results in Table 4 change very little: *Twitter Firm* is insignificant in models (1)-(3), and significant in models (4)-(6) with coefficients of 2.01, 2.35, and 2.55 (compared to coefficients of 2.02, 2.39, and 2.57, respectively, in models (4)-(6) of Table 4). *EPS Announcement Return* is insignificant in all six models.

Panel B results are similar in that the results do not qualitatively change from those in Table 5, and *EPS Announcement Return* is consistently insignificant. Likewise, results in panels C and D show that results in Table 6 are not qualitatively affected by including *EPS Announcement Return*. The results in panel C are particularly interesting because the significance of *Ln(1+No. of Earnings Tweets)* after controlling for *EPS Announcement Return* shows that impact of tweeting about earnings on post-announcement returns is not fully explained by its potential impact on the initial stock price reaction at the announcement. This result is consistent with tweeting about negative earnings raising awareness, and helping to influence investors to buy during the post-announcement period (thus pushing prices higher). Such a channel would be in line with the findings in Hirshleifer, Myers, Myers, and

Teoh (2008) that retail investors tend to buy following not only extreme positive earnings news, but negative earnings news as well.

Panels E through F change the market benchmark in the post-announcement return calculations to the CRSP value-weighted return with dividends. We argue that the equal-weighted return (used in the earlier analysis) is a more natural benchmark for a firm chosen at random, because the value-weighted return is skewed toward large firms. However, it is worth investigating the extent to which our main results are sensitive to this choice. Not surprisingly given that the average Twitter firm is larger than the average non-Twitter firm (see Table 1), panel E shows smaller magnitudes for the coefficients on *Twitter Firm* than in Table 4. However, the key coefficients remain economically and statistically significant.

When this robustness analysis focuses on Twitter firms and the effect of *Tweet Intensity* and *No. of Twitter Followers*, results are stronger both economically and statistically. Panel F not only shows stronger results for Q1 announcements, but also shows significant results for Q5 announcements as well.

Panel G focuses on the results in Table 6, panel A for earnings tweets during days -45 to +1 for Q1 announcements. The number of earnings tweets is insignificant in models (1)-(3), but continues to correlate with post-announcement returns in model (4) once we control for *Ln(No. of Followers)*. In model (5) the interaction between *Ln(No. of Followers)* and *Ln(1 + No. of Earnings Tweets)* remains economically significant, and is statistically more significant than in panel A of Table 6. Models (6)-(8) have largely similar results to those in Table 6.

Panel H, which counts earnings tweets over days +2 to +45, shows qualitatively similar results to those in panel B of Table 6, except that *Ln(Tweet Intensity)* is now significant in models (2) and (3), and the statistical significance of *Ln(1+No. of Earnings Tweets)* is stronger in six of the eight models. Overall, panels E through H show that the nature of the results in Tables 4 through 6 is robust to using the CRSP value-weighted return as the market benchmark.

4.4. Conclusion

Social media could impact the way stock prices respond to corporate news by mitigating or exacerbating the limited attention of investors, or by influencing the way investors process and perceive such news. We compare the post-earnings announcement returns of firms that are active on Twitter to those that are not. To summarize the results for extreme negative earnings news, in the period in which Twitter becomes popular there is weak, negative post-earnings announcement drift (PEAD) in the returns of non-Twitter firms, but strong, *positive* return drift in the returns of Twitter firms. This finding appears to have an industry structure because returns do not statistically differ after controlling for industry fixed effects. The difference survives controlling only for firm-specific characteristics, however, and during a placebo, pre-Twitter period univariate post-announcement returns do not statistically differ between firms that later become active on Twitter and those that do not. Moreover, in the period of Twitter popularity, post-announcement returns following extreme negative earnings news for Twitter firms are more positive when the firm tweets more often, has a larger Twitter audience, and specifically tweets about its earnings.

These results suggest that when firms have extreme negative earnings news, a firm's use of social media either helps to cause an overreaction at the announcement, or attracts investors who *perceive* an overreaction and are thus induced to buy the firm's stock. Therefore, although social media appears to mitigate limited attention of investors to negative earnings news, it does not necessarily do so in a way that improves the efficiency of how stock prices react.

Results for positive earnings news are less clear. Twitter firms experience stronger PEAD in the direction of the news than non-Twitter firms, even after controlling for firm characteristics and industry fixed effects. However, the marginal effect is invariant to the nature of the firm's Twitter activity and audience size, which points toward a firm's choice to be active on Twitter as proxying for characteristics that are not controlled for by easily-measurable firm-level variables.

The behavioral economics literature highlights that utility functions are asymmetric in gains and losses. Our findings imply that a firm's social media activity has an asymmetric effect on investor reaction to extreme positive versus negative news. One possible explanation relates to retail investors, who are likely gravitate toward trading the stocks of social media-active firms due to familiarity or firm characteristics that correlate with a firm's choice to use social media. The finding in Hirshleifer, Lim, and Teoh (2009) that retail investors buy in reaction to both positive and negative extreme earnings news, despite the disparate direction of the news, implies that such investors process positive and negative news differently. In light of this implication, it is perhaps not surprising that a firm's social media use differentially impacts post-earnings announcement returns following positive and negative earnings news.

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Table 1
Summary Statistics

This table reports firm-level summary statistics for Twitter and non-Twitter firms in panels A and B, respectively. Twitter firms are those with accounts that have a *Twitter Intensity* of at least 0.10, signifying the firm has tweeted an average of at least once every ten days over the life of its account(s). For the 2008 and 2011 statistics, firms are classified as Twitter and non-Twitter firms based on their status at the time of the fiscal year-end data in Compustat. *No. of Twitter Followers* is coded on an ex post basis and is the number of Twitter users following the firm's tweets as of March 1, 2013. All continuous variables are winsorized at the 1% level on both tails.

Panel A: Twitter Firms

	(Placebo) 2004 (N=489)		2008 (N=131)		2011 (N=569)	
Variable:	**Mean**	**Std. Dev**	**Mean**	**Std. Dev**	**Mean**	**Std. Dev**
Tweet Intensity	-	-	4.12	15.54	4.17	15.44
No. of Twitter Followers	-	-	150,272	595,171	114,436	593,383
Book Assets ($M)	7,180	22,267	10,783	15,379	10,838	41,365
M/B	2.47	1.62	2.70	2.25	2.13	1.29
Cash/Assets	0.21	0.21	0.22	0.19	0.22	0.19
Has R&D Expense	0.53	0.50	0.55	0.51	0.54	0.50
Dividend Paying	0.41	0.49	0.35	0.49	0.39	0.49
Leverage	0.36	0.24	0.35	0.25	0.33	0.24
(PP&E + Inv)/Assets	0.11	0.12	0.09	0.12	0.12	0.14
Institutional Block Ownership	0.15	0.14	0.21	0.17	0.21	0.16
Advertising/Sales	0.03	0.04	0.05	0.05	0.03	0.04

Panel B: Non-Twitter Firms

	(Placebo) 2004 (N=2,326)		2008 (N=2,727)		2011 (N=2,034)	
Variable:	**Mean**	**Std. Dev**	**Mean**	**Std. Dev**	**Mean**	**Std. Dev**
Book Assets ($M)	5,606	35,988	9,097	74,073	10,670	89,677
M/B	2.02	1.45	1.98	1.40	1.76	1.25
Cash/Assets	0.20	0.23	0.20	0.23	0.20	0.22
Has R&D Expense	0.43	0.50	0.44	0.50	0.41	0.49
Dividend Paying	0.45	0.50	0.45	0.50	0.47	0.50
Leverage	0.29	0.26	0.30	0.26	0.30	0.27
(PP&E + Inv)/Assets	0.14	0.15	0.14	0.15	0.14	0.16
Institutional Block Ownership	0.13	0.14	0.20	0.16	0.18	0.15
Advertising/Sales	0.02	0.03	0.02	0.04	0.02	0.04

Table 2
Univariate Post-Announcement Returns

Each month, all earnings announcements in that month are ranked into quintiles based on the earnings surprise, calculated as the actual earnings minus the median analyst forecast earnings, divided by the stock price one week prior. The table reports the mean cumulative abnormal return from day +2 to day +60 after all earnings announcements in the specified subgroup (in % units). For the Placebo, Pre-Twitter period (2004-2006Q1), the column labeled Eventual Twitter-Firm contains statistics for EPS observations by firms that later became Twitter firms. For the later two time periods, observations are classified based on the firm's Twitter status at the time of the earnings announcement. Two-sided *t*-statistics are reported below each abnormal return in parenthesis. The second to last row reports the difference in the post-announcement abnormal returns between the highest (Q5) and lowest (Q1) quintile earnings announcements in each period, and the last row reports the *t*-statistic for this difference. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	All EPS Announcements			**Placebo, Pre-Twitter Period (2004-2006Q1)**		**Early-Twitter Period (2006Q2-2008)**		**Mature-Twitter Period (2009-2011)**	
Announcement Quintile	Pre-Twitter (2004-2006Q1)	Early Twitter (2006Q2-2008)	Mature Twitter (2009-2011)	Non-Twitter-Firms	Eventual Twitter-Firm	Non-Twitter-Firm	Twitter-Firm	Non-Twitter-Firm	Twitter-Firm
	(%)	(%)	(%)	(%)	(%)	(%)	(%)	(%)	(%)
Q1 (lowest)	-1.28***	-1.49***	-0.32	-1.31***	-1.10*	-1.52***	0.72*	-0.50*	2.05**
	(-5.42)	(-4.93)	(-1.14)	(-5.15)	(-1.72)	(-5.03)	(1.66)	(-1.65)	(2.02)
Q2	-0.83***	-0.88***	-0.25	-0.86***	-0.70	-0.90***	1.00	-0.41	0.64
	(-4.06)	(-3.39)	(-1.01)	(-3.78)	(-1.51)	(-3.44)	(0.33)	(-1.51)	(1.27)
Q3	-0.18	0.50**	-0.42*	-0.24	0.03	0.51**	-0.59	-0.85***	0.14
	(-0.77)	(2.12)	(-1.85)	(-0.90)	(0.07)	(2.16)	(-0.32)	(-3.21)	(0.83)
Q4	0.49**	0.34	-0.26	0.55**	0.26	0.35	-0.05	-0.45	0.41
	(2.22)	(1.42)	(-1.12)	(2.18)	(0.59)	(1.44)	(-0.02)	(-1.63)	(0.97)
Q5 (highest)	1.38***	0.73***	0.43*	1.28***	1.88***	0.72***	1.43	0.24	1.27***
	(5.95)	(2.71)	(1.71)	(4.88)	(3.80)	(2.65)	(0.92)	(0.84)	(2.66)
Q5-Q1	2.66***	2.22***	0.75**	2.58***	2.98***	2.24***	0.71	0.74*	-0.78
t-stat.	(8.03)	(5.48)	(1.99)	(7.08)	(3.75)	(5.51)	(1.03)	(1.76)	(-0.30)

Table 3
Multivariate Regressions Analysis of Post-Announcement Returns

This table reports OLS regressions where the dependent variable is the cumulative abnormal return over days +2 to +60 after an earnings announcement (in % units, winsorized at the 1% level at both tails). Each month, all announcements in that month are sorted into quintiles based on the earnings surprise (the actual earnings minus the median analyst forecast, divided by the stock price one week prior). (Q1) and (Q5) denote the lowest and highest quintiles, respectively. *Twitter Firm* is an indicator set to one for EPS observations by firms that tweet at least once every ten days over the life of their account(s) and opened their account open at the time of the EPS announcement. *Became Twitter Firm* is an indicator set to one for an EPS announcement during the pre-Twitter period by a firm that later became a Twitter firm. Except for the indicator variables *Has R&D Expense* and *Dividend Paying,* all variables are winsorized at the 1% level on both tails. Heteroskedasticity-robust *t-statistics* are in parenthesis, and statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Time Period:	(Placebo) Pre-Twitter (2004-2006Q1)		Early Twitter (2006Q2-2008)		Mature Twitter (2009-2011)	
Announcement Quintile:	Q1	Q5	Q1	Q5	Q1	Q5
Became Twitter Firm	-0.15	0.68				
	(-0.21)	(1.15)				
Twitter Firm			3.14	1.56	1.46**	1.84***
			(0.92)	(0.95)	(1.99)	(3.21)
Ln (Book Assets)	0.20	-0.41***	0.45**	-0.34**	0.41**	-0.85***
	(1.28)	(-2.63)	(2.25)	(-1.97)	(2.20)	(-5.27)
M/B	-0.38	-0.49*	-0.29	-0.54**	0.15	-1.04***
	(-1.33)	(-1.92)	(-0.91)	(-2.06)	(0.37)	(-3.01)
Cash/Assets	0.29	-6.57***	3.98*	-2.26	2.73	1.84
	(0.15)	(-3.92)	(1.88)	(-1.25)	(1.40)	(0.87)
Has R&D Expense	0.40	-0.56	1.25*	-0.17	2.44***	1.78***
	(0.70)	(-1.07)	(1.82)	(-0.28)	(3.49)	(3.36)
Dividend Paying	-0.29	-1.09**	1.08	1.03	-1.24*	0.12
	(-0.53)	(-2.04)	(1.53)	(1.61)	(-1.94)	(0.22)
Leverage	3.77***	3.52***	3.12**	-0.86	3.35***	0.14
	(4.04)	(3.83)	(2.52)	(-0.71)	(2.93)	(0.12)
(PP&E + Inv)/Assets	0.92	0.42	-6.71***	-1.67	9.92***	9.96***
	(0.46)	(0.21)	(-2.60)	(-0.70)	(4.71)	(5.00)
Institutional Block Ownership	0.89	0.57	0.59	-1.10	1.85	-2.85
	(0.56)	(0.34)	(0.35)	(-0.64)	(1.02)	(-1.59)
Constant	-3.49**	5.86***	-5.87***	4.95***	-7.48***	5.54***
	(-2.49)	(4.10)	(-3.32)	(2.98)	(-4.42)	(3.39)
Observations	4,342	4,371	5,227	5,233	5,349	5,516
R-squared	0.01	0.02	0.01	0.00	0.02	0.02

Table 4
Multivariate Regression Analysis of Post-Announcement Returns in
Mature-Twitter Period (2009-2011) Controlling for Industry Fixed Effects and Advertising

This table reports OLS regressions where the dependent variable is the cumulative abnormal return over days +2 to +60 after an earnings announcement (in % units, winsorized at the 1% level at both tails). The sample period for all regressions is the Mature-Twitter Period (2009-2011). Each month, all announcements in that month are ranked into quintiles based on the earnings surprise, calculated as the actual earnings minus the median analyst forecasted earnings, divided by the stock price one week prior. Columns 1-3 restrict the sample to the lowest quintile announcements (Q1) while 4-6 restrict the sample to the highest quintile announcements (Q5). *Twitter Firm* is an indicator equal to 1 if the EPS observation is for a firm with a twitter handle that tweets on average at least once every ten days. Fixed effects for the Fama-French 49 industries are included (but not shown below) in columns 1,3,4, and 6. Except for the indicator variables *Has R&D Expense* and *Dividend Paying*, all variables are winsorized at the 1% level on both tails. Heteroskedasticity-robust *t-statistics* are in parenthesis, and statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Announcement Quintile (1=lowest):	Quintile 1 (lowest)			Quintile 5 (highest)		
Twitter Firm	0.94	0.32	-0.57	2.02***	2.39***	2.57***
	(0.16)	(0.27)	(-0.45)	(3.15)	(2.81)	(2.77)
Ln (Book Assets)	0.41**	0.45	0.61*	-0.88***	-0.61***	-0.69***
	(2.05)	(1.44)	(1.90)	(-5.17)	(-2.58)	(-2.77)
M/B	0.12	-0.07	-0.40	-0.85**	-0.50	-0.16
	(0.29)	(-0.11)	(-0.56)	(-2.30)	(-1.05)	(-0.32)
Cash/Assets	2.03	2.83	3.48	3.67	0.03	-0.16
	(0.94)	(0.90)	(0.93)	(1.64)	(0.01)	(-0.05)
Has R&D Expense	-0.66	2.68**	-0.66	1.72*	1.25	0.97
	(-0.63)	(2.43)	(-0.36)	(1.78)	(1.55)	(0.70)
Dividend Paying	-1.08	-0.60	-0.06	-0.18	-0.09	-0.20
	(-1.58)	(-0.56)	(-0.05)	(-0.31)	(-0.11)	(-0.22)
Leverage	0.84	8.22***	5.59	-0.58	-0.15	0.18
	(0.44)	(3.93)	(1.64)	(-0.30)	(-0.08)	(0.05)
(PP&E + Inv)/Assets	13.09***	10.31***	13.78***	11.29***	9.82***	10.67***
	(5.99)	(3.00)	(3.80)	(5.28)	(3.17)	(3.24)
Institutional Block Ownership	0.45	0.93	0.28	-3.15*	-0.77	-1.10
	(0.24)	(0.33)	(0.09)	(-1.70)	(-0.28)	(-0.39)
Advertising/Sales		8.52	8.15		1.99	4.68
		(0.59)	(0.52)		(0.19)	(0.40)
Constant	-5.88***	-9.34***	-9.06***	5.34***	2.97	2.94
	(-3.06)	(-3.46)	(-3.06)	(2.88)	(1.24)	(1.08)
Observations	5,349	2,370	2,370	5,516	2,408	2,408
R-squared	0.04	0.03	0.05	0.03	0.01	0.04
Industry fixed effects	Yes	No	Yes	Yes	No	Yes

Table 5
The Effect of Tweeting Intensity and Twitter Followers for Twitter Firms

This table reports OLS regressions where the dependent variable is the cumulative abnormal return over days +2 to +60 after an earnings announcement (in % units, winsorized at the 1% level at both tails). The sample period for all regressions is the Mature-Twitter Period (2009-2011). Columns 1-4 restrict the sample to the lowest quintile announcements (Q1) while 4-8 restrict the sample to the highest quintile announcements (Q5). *Tweet Intensity* is the average number of tweets per day, and *No. of Twitter Followers* is the number of Twitter users following the firm's tweets. All regressions include industry fixed effects. Except for the indicator variables *Has R&D Expense* and *Dividend Paying*, all variables are winsorized at the 1% level on both tails. Heteroskedasticity-robust *t-statistics* are in parenthesis, and statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Announcement Quintile:	Quintile 1 (lowest)				Quintile 5 (highest)			
Ln(Tweet Intensity)	1.24*		0.09	3.23	0.60		0.21	0.57
	(1.69)		(0.10)	(1.35)	(1.39)		(0.41)	(0.32)
Ln(No. of Twitter Followers)		1.34**	1.31*	1.59**		0.59	0.50	0.53
		(2.32)	(1.83)	(2.05)		(1.62)	(1.14)	(1.14)
Ln(Tweet Intensity)* Ln(No. of Twitter Followers)				-0.34				-0.04
				(-1.43)				(-0.21)
Ln (Book Assets)	-0.02	-0.60	-0.59	-0.65	-0.86**	-1.14**	-1.12**	-1.13**
	(-0.03)	(-0.87)	(-0.84)	(-0.92)	(-2.14)	(-2.29)	(-2.21)	(-2.21)
M/B	-0.41	-0.40	-0.40	-0.39	0.22	0.18	0.17	0.18
	(-0.34)	(-0.32)	(-0.32)	(-0.31)	(0.30)	(0.24)	(0.23)	(0.24)
Cash/Assets	-9.37	-10.21	-10.21	-9.74	3.53	2.23	2.37	2.42
	(-1.27)	(-1.36)	(-1.36)	(-1.30)	(0.70)	(0.43)	(0.45)	(0.46)
Has R&D Expense	1.14	1.00	0.98	0.33	0.44	0.36	0.40	0.37
	(0.40)	(0.34)	(0.34)	(0.11)	(0.21)	(0.17)	(0.19)	(0.18)
Dividend Paying	-1.65	-1.19	-1.21	-1.09	0.56	0.57	0.61	0.60
	(-0.89)	(-0.64)	(-0.65)	(-0.58)	(0.44)	(0.45)	(0.49)	(0.48)
Leverage	1.55	3.83	3.85	4.18	3.78	3.50	3.63	3.68
	(0.29)	(0.70)	(0.71)	(0.76)	(0.92)	(0.85)	(0.88)	(0.89)
(PP&E + Inv)/Assets	6.28	8.40	8.33	8.60	6.46	7.23	7.12	7.16
	(0.97)	(1.32)	(1.29)	(1.33)	(1.28)	(1.45)	(1.43)	(1.43)
Institutional Block Ownership	-0.92	0.58	0.49	1.07	-2.20	-1.91	-1.97	-1.94
	(-0.18)	(0.11)	(0.10)	(0.20)	(-0.56)	(-0.49)	(-0.50)	(-0.50)
Constant	1.62	-7.41	-7.12	-8.74	4.19	1.50	2.04	1.78
	(0.26)	(-1.17)	(-1.04)	(-1.25)	(0.93)	(0.34)	(0.46)	(0.38)
Observations	639	639	639	639	1,009	1,009	1,009	1,009
R-squared	0.08	0.08	0.08	0.08	0.04	0.04	0.04	0.04
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 6
The Effect of Earnings-Related Tweets around Negative Earnings News for Twitter Firms

This table reports OLS regressions where the dependent variable is the cumulative abnormal return over days +2 to +60 after an earnings announcement (in % units, winsorized at the 1% level at both tails) for negative earnings surprises (Q1). The sample period for both panels is the Mature-Twitter period (2009-2011). *No. of Earnings Tweets* is the number of tweets containing the word earnings during days -45 to +1 around the earnings announcement (Panel A) or during days +2 to +25 (Panel B). All regressions include industry fixed effects and the other control variables used in Table 5. For brevity we do not report these variables or the constant term. Heteroskedasticity-robust *t-statistics* are in parenthesis, and statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Panel A: *No.of Earnings Tweets* counted during days [-45,+1]

	(1)	(2)	(3)	(4)	(5)
Ln (1+ No. of Earnings Tweets)	5.09**	4.93*	4.29*	5.96**	-15.67
	(2.03)	(1.94)	(1.66)	(2.40)	(-1.25)
Ln(Tweet Intensity)		1.16	0.99		
		(1.57)	(1.33)		
Ln(Tweet Intensity) * Ln(1+No. of Earnings Tweets)			2.31		
			(1.15)		
Ln(No. of Followers)				1.46**	1.34**
				(2.52)	(2.37)
Ln(No. of Followers) * Ln (1+No. of Earnings Tweets)					2.56*
					(1.81)
Other controls & Industry FF	Yes	Yes	Yes	Yes	Yes
Observations	639	639	639	639	639
R-squared	0.08	0.08	0.08	0.09	0.09

Panel B: *No.of Earnings Tweets* counted during days [+2,+45]

	(1)	(2)	(3)	(4)	(5)
Ln (1+ No. of Earnings Tweets)	9.94*	9.17*	8.53*	9.88*	38.12**
	(1.86)	(1.83)	(1.87)	(1.72)	(2.30)
Ln(Tweet Intensity)		1.16	1.13		
		(1.57)	(1.53)		
Ln(Tweet Intensity) * Ln(1+No. of Earnings Tweets)			5.15*		
			(1.96)		
Ln(No. of Followers)				1.36**	1.41**
				(2.34)	(2.43)
Ln(No. of Followers) * Ln (1+No. of Earnings Tweets)					-3.53
					(-1.64)
Other controls & Industry FF	Yes	Yes	Yes	Yes	Yes
Observations	639	639	639	639	639
R-squared	0.07	0.08	0.08	0.08	0.09

Table 7
Robustness: Using Value-Weighted Market Returns as the Benchmark and Controlling for Announcement Returns

The table repeats regressions in Tables 4-6 with two distinct robustness checks: Panels A-D repeat Tables 4, 5, and 6 (Panels A and B) with the additional inclusion of *EPS Announcement Return* (the CAR measured over days -2 to +1) as a control variable, and Panels D-F repeat Tables 4, 5, and 6 (Panels A and B) where the dependent variable CARS (post-announcement returns) cumulate abnormal returns calculated based on value-weighted CRSP returns instead of equal-weighted. See Tables 4-6 for the control variables included that are not reported below for brevity. For brevity we do not report these variables or the constant term. Heteroskedasticity-robust *t-statistics* are in parenthesis, and statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Panel A: Replication of Table 4 controlling for *EPS Announcement Return*

	(1)	(2)	(3)	(4)	(5)	(6)
Announcement Quintile (1=lowest):		Quintile 1			Quintile 5	
Twitter Firm	1.14	0.30	0.60	2.01***	2.35***	2.55***
	(1.25)	(1.16)	(1.17)	(3.13)	(2.77)	(2.74)
Advertising/Sales		8.37	8.02		1.87	4.75
		(0.58)	(0.51)		(0.18)	(0.40)
EPS Announcement Return	0.01	0.05	0.05	0.04	0.06	0.06
	(0.18)	(0.81)	(0.79)	(1.05)	(1.22)	(1.25)
Observations	5,349	2,370	2,370	5,516	2,408	2,408
R-squared	0.04	0.03	0.05	0.03	0.01	0.04
Industry fixed effects	Yes	No	Yes	Yes	No	Yes

Panel B: Replication of Table 5 controlling for *EPS Announcement Return*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Announcement Quintile:	Quintile 1				Quintile 5			
Ln(Tweet Intensity)	1.20*		0.08	3.20	0.57		0.19	0.53
	(1.67)		(0.09)	(1.34)	(1.31)		(0.36)	(0.30)
Ln(No. of Followers)		1.36**	1.33*	1.60**		0.57	0.49	0.52
		(2.35)	(1.85)	(2.07)		(1.57)	(1.12)	(1.12)
Ln(Tweet Intensity) *				0.34				-0.04
Ln(No. of Followers)				(1.42)				(-0.20)
EPS Announcement Return	0.04	0.05	0.05	0.05	0.06	0.06	0.05	0.05
	(0.40)	(0.46)	(0.46)	(0.45)	(0.80)	(0.80)	(0.79)	(0.78)
Observations	639	639	639	639	1,009	1,009	1,009	1,009
R-squared	0.08	0.08	0.08	0.08	0.04	0.04	0.04	0.04

Panel C: Replication of Table 6, Panel A, controlling for *EPS Announcement Return*

	(1)	(2)	(3)	(4)	(5)
Ln (1+ No. of Earnings Tweets)	5.09**	4.93*	4.29*	5.96**	-15.67
	(2.03)	(1.94)	(1.66)	(2.40)	(-1.25)
Ln(Tweet Intensity)		1.16	0.99		
		(1.57)	(1.33)		
Ln(Tweet Intensity) *			2.31		
Ln(1+No. of Earnings Tweets)			(1.15)		
Ln(No. of Followers)				1.46**	1.34**
				(2.52)	(2.37)
Ln(No. of Followers) *					2.56*
Ln (1+No. of Earnings Tweets)					(1.81)
EPS Announcement Return	0.04	0.05	0.05	0.06	0.07
	(0.40)	(0.42)	(0.47)	(0.50)	(0.59)
Observations	639	639	639	639	639
R-squared	0.08	0.08	0.08	0.09	0.09

Panel D: Replication of Table 6, Panel B, controlling for *EPS Announcement Return*

	(1)	(2)	(3)	(4)	(5)
Ln (1+ No. of Earnings Tweets)	9.94*	9.17*	8.53*	9.88*	38.12**
	(1.86)	(1.83)	(1.87)	(1.72)	(2.30)
Ln(Tweet Intensity)		1.16	1.13		
		(1.57)	(1.53)		
Ln(Tweet Intensity) *			5.15*		
Ln(1+No. of Earnings Tweets)			(1.96)		
Ln(No. of Followers)				1.36**	1.41**
				(2.34)	(2.43)
Ln(No. of Followers) *					-3.53
Ln (1+No. of Earnings Tweets)					(-1.64)
EPS Announcement Return	0.04	0.04	0.04	0.05	0.04
	(0.32)	(0.35)	(0.37)	(0.41)	(0.41)
Observations	639	639	639	639	639
R-squared	0.07	0.08	0.08	0.08	0.09

Panel E: Replication of Table 4 using the CRSP Value-Weighted Market as the Benchmark in CAR Calculations

	(1)	(2)	(3)	(4)	(5)	(6)
Announcement Quintile (1=lowest):		Quintile 1			Quintile 5	
Twitter Firm	1.00	0.50	1.67	1.28***	1.08*	1.73*
	(1.05)	(0.39)	(1.22)	(2.42)	(1.72)	(1.77)
Advertising/Sales		13.52	12.77		6.12	7.81
		(0.90)	(0.79)		(0.55)	(0.63)
Observations	5,349	2,370	2,370	5,516	2,408	2,408
R-squared	0.04	0.03	0.06	0.04	0.02	0.04
Industry (FF-49) FE	Yes	No	Yes	Yes	No	Yes

Panel F: Replication of Table 5 using the CRSP Value-Weighted Market as the Benchmark in CAR Calculations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Quintile 1				Quintile 5		
Ln(Tweet Intensity)	1.82**		0.34	3.62	0.85*		0.08	0.29
	(2.38)		(0.36)	(1.47)	(1.91)		(0.15)	(0.17)
Ln(No. of Followers)		1.88***	1.74**	2.03**		1.02***	0.98**	1.00**
		(3.11)	(2.32)	(2.51)		(2.71)	(2.16)	(2.08)
Ln(Tweet Intensity) *				0.35*				-0.02
Ln(No. of Followers)				(1.65)				(-0.12)
Observations	639	639	639	639	1,009	1,009	1,009	1,009
R-squared	0.09	0.10	0.10	0.10	0.05	0.06	0.06	0.06

Panel G: Replication of Table 6, Panel A using the CRSP Value-Weighted Market as the Benchmark in CAR Calculations

	(1)	(2)	(3)	(4)	(5)
Ln (1+ No. of Earnings Tweets)	4.15	3.89	3.35	5.30**	-12.11
	(1.62)	(1.50)	(1.25)	(2.10)	(-0.96)
Ln(Tweet Intensity)		1.78**	1.64**		
		(2.33)	(2.10)		
Ln(Tweet Intensity) *			1.97		
Ln(1+No. of Earnings Tweets)			(1.00)		
Ln(No. of Followers)				1.97***	1.87***
				(3.26)	(3.15)
Ln(No. of Followers) *					2.06**
Ln (1+No. of Earnings Tweets)					(2.15)
Observations	639	639	639	639	639
R-squared	0.08	0.09	0.09	0.10	0.10

Panel H: Replication of Table 6, Panel B using CRSP Value-Weighted Market as the Benchmark in CAR Calculations

	(1)	(2)	(3)	(4)	(5)
Ln (1+No. of Earnings Tweets)	10.72**	9.57**	8.95**	10.73**	32.05**
	(2.15)	(2.17)	(2.34)	(2.02)	(2.08)
Ln(Tweet Intensity)		1.77**	1.75**		
		(2.32)	(2.28)		
Ln(Tweet Intensity) * Ln(1+No. of Earnings Tweets)			5.13**		
			(2.27)		
Ln(No. of Followers)				1.88***	1.92***
				(3.10)	(3.14)
Ln(No. of Followers) * Ln (1+No. Earnings Tweets)					-2.66
					(-1.40)
Observations	639	639	639	639	639
R-squared	0.08	0.09	0.09	0.10	0.10

Figure 1
Growth in Twitter Accounts

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