Can Twitter Help Predict Firm-Level Earnings and Stock Returns?

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Abstract

Prior research examines how companies exploit Twitter in communicating with investors, how information in tweets by individuals may be used to predict the stock market as a whole, and how Twitter activity relates to the response to earnings news. In this study, we investigate whether analyzing the aggregate opinion in individual tweets about a company's prospects can predict its earnings and the stock price reaction to them. Our dataset contains 998,495 tweets (covering 34,040 firm-quarters from 3,662 distinct firms) by individuals in the nine-trading-day period leading to firms' quarterly earnings announcements in the four-year period, January 1, 2009 to December 31, 2012. Using four alternative measures of aggregate opinion in individual tweets, we find that the aggregate opinion successfully predicts the company's forthcoming quarterly earnings. We also document a positive association between the aggregate opinion and the abnormal stock price reaction to the quarterly earnings announcement. These findings are more pronounced for firms in weaker information environments (small firms, firms with low analyst following and less press coverage), and robust to specifications that consider a variety of control variables. Overall, these findings highlight the importance for financial market participants to consider the aggregate information on Twitter when assessing the future prospects and value of companies.

Keywords: Wisdom of Crowds, Twitter, social media, earnings, analyst earnings forecast, abnormal returns.

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1. Introduction

Investors have long relied on intermediaries such as financial analysts to acquire timely and value-relevant information regarding the prospects of the stocks they are interested in. Yet, prior research has identified several issues with the information provided by financial analysts. For instance, analyst coverage is often limited to large, actively traded firms with high levels of institutional ownership (e.g., O'Brien and Bhushan 1990). Additionally, analysts often provide dated and stale information, which does not incorporate the latest news related to the firms they cover (Brown 1991). A lengthy stream of research has also shown that analyst reports are biased and affected by the conflict of interests they face (e.g., Dugar and Nathan 1995, Lin and McNichols 1998, Michaely and Womack 1999).

The past decade has seen an explosion in alternate sources of information available to capital market participants. In particular, individual investors no longer rely solely on financial intermediaries or the business press for timely and value-relevant information. With the advent of the Internet, and recently of social media, individual investors increasingly rely on each other. For instance, Antweiler and Frank (2004) show that messages posted by investors on Internet bulletin boards such as Yahoo Finance and the Raging Bull are associated with market volatility. Similarly, Chen et al. (2014) demonstrate that the insights provided in user generated research reports on the SeekingAlpha portal help predict earnings and stock returns.

By far, the biggest revolution in the dissemination of information on the Internet has taken place with the advent of social media platforms, which allow users to instantaneously post their views about stocks and their prospects to a wide audience. Of all social media platforms, Twitter specifically stands out as a primary tool used by individuals to share information, given its popularity and ease of use. In fact, the importance of Twitter as a valuable source of information has not gone unnoticed by practitioners. For example, a recent CNN online article quotes Paul Hawtin—the founder of the investment management firm Cayman Atlantic, who has been working on a fund based exclusively on analyzing tweets for relevance and sentiment to base trades on—as saying, "Analyzing untapped and unstructured datasets such as Twitter gives us a distinct advantage over other investment managers."[1]

Recently, the academic literature has started studying the role of Twitter and its impact on the capital market and market participants. One strand of this recent literature investigates how companies exploit this new channel to communicate with investors. For example, Blankespoor et al. (2014) show that firms can reduce information asymmetry by more broadly disseminating their news through Twitter by sending market participants links to press releases provided via traditional disclosure methods. Jung et al. (2015) find that roughly half of S&P 1,500 firms have created either a corporate Twitter account or Facebook page, with a growing preference for Twitter.[2] Lee et al. (2014) show that firms use social media channels such as Twitter to interact with investors in order to attenuate the negative price reactions to consumer product recalls. Another strand of this literature investigates whether investor mood derived from analyzing text content of Twitter predicts the overall stock market. Bollen et al. (2011) show that aggregate investor model inferred from the textual analysis of daily Twitter feeds can help predict changes in the Dow Jones index. Similarly, Mao et al. (2012) find that the daily number of tweets that mention S&P 500 stocks is significantly correlated with S&P 500 levels, changes and absolute changes. Finally, a third strand of this literature analyzes how investor activity on Twitter, can influence investor response to

[1] CNN, BusinessNext Article, updated Sep 1, 2014 12:41 GMT, "How traders track Twitter to beat the market." http://www.cnn.com/2014/08/29/business/how-traders-track-twitter/

[2] In June of 2015, the SEC's staff, in a "Compliance and Disclosure Interpretations," said a startup can post a Twitter message about its stock or debt offering to gauge interest among potential investors. This announcement continues the agency's trend of warming up to social media, which began in April 2013 when it approved the use of posts on Facebook and Twitter to communicate corporate announcements such as earnings.

earnings news. A contemporaneous study, Curtis et al. (2014), finds that high levels of Twitter activity by investors are associated with greater sensitivity of earnings announcement returns to earnings surprises, while low levels of Twitter activity are associated with significant post-earnings-announcement drift.

In this study, we examine the predictive ability of investor opinions expressed on Twitter by investigating the following three questions: (1) Does the aggregate opinion in individual tweets regarding a company's prospects predict its quarterly earnings? (2) Does the aggregate opinion predict the stock price reaction to the earnings news? And (3) Does the information environment explain the cross sectional variation in the predictive ability of the aggregate opinion in individual tweets (if it exists)?

Ex-ante, there are a number of reasons to believe that information on Twitter might have limited usefulness for the prediction of firm-level earnings and stock returns. For instance, the information in Twitter might lack credibility as anyone can set up a Twitter account and tweet anonymously about any stock. Individuals can then reply or retweet the information initially posted. Twitter has no mechanism to monitor the information tweeted or to incentivize high quality information. This is in sharp contrast to investing portals such as SeekingAlpha that publish full length reports from registered users after verifying their credentials and vetting the quality of the submissions. Further, the information in Twitter not be accurate, with several documented instances of users misleading markets through false and misleading tweets.[3] Finally, tweets are restricted to a mere 140 characters, in contrast to information from other sources, including other social media platforms. This potentially limits the ability of the sender to convey

[3] There have been instances of Twitter users misleading entire markets with false information. In 2010, the Australian airline Qantas saw its stock price decline by more than 10% after false reports of a plane crash appeared on Twitter. Similarly, in 2013, a fake tweet claiming that President Obama had been injured in an explosion at the White House lead to a 0.9% decline in the value of the S&P 500, representing $130 billion in stock value.

value-relevant information, or at the very least constrains the sender's ability to provide facts and analyses to support the information.

Despite the potential for intentional or unintentional misleading information provided, there are at least four reasons why Twitter might provide value relevant and timely information. First, Twitter allows one to tap into the "wisdom of the crowds." The Wisdom of Crowds concept refers to a phenomenon first observed by Sir Francis Galton more than a century ago, that a large group of problem-solvers often makes a better collective prediction than that produced by experts. Secondly, Twitter provides a source of information from an extremely diverse set of individuals. Hong and Page (2004) show analytically that a group of diverse problem solvers can outperform groups of homogenous high-ability problem solvers. Tweets by individuals regarding a firm's future prospects provide a source of information that relies on both a large number as well as a diverse set of information providers. This contrasts sharply with the small number of analysts providing research reports, and their rather homogenous backgrounds in terms of demographics and education (Cohen et al. 2010). Third, users in Twitter are more likely to be independent and less likely to "herd" to the consensus viewpoint, unlike analysts (Jegadeesh and Kim 2010) and in contrast with other social media platforms (e.g., blogs, investing portals, etc.), where a central piece of information is posted and users simply comment on this information. Finally, the short format of tweets and ease of search for information on Twitter with the use of hashtags (#) and cashtags ($) might make it an ideal medium to share breaking news, in contrast to the longer format and potentially reduced timeliness of research reports or articles.[4]

To study our three research questions, we analyze a broad sample of 998,495 tweets (covering 34,040 firm-quarters from 3,662 distinct Russell 3000 firms), in the nine-trading-day

[4] A recent study by Osborne and Dredze (2014) confirms that Twitter is the best portal for breaking news, as opposed to alternatives like Facebook and Google Plus, which mostly repost newswire stories and package multiple sources of information together.

period leading up to the quarterly earnings announcement (days -10 to -2, where day 0 is the earnings announcement day), in which individuals opine on a firm's prospects. The sample spans the four-year period, January 1, 2009 to December 31, 2012.

Briefly, we document three sets of findings. With respect to our first research question, we demonstrate the ability of aggregate opinion in individual tweets regarding a company just prior to the earnings announcement to predict the company's quarterly earnings. Next, we document a positive association between our measures of aggregate tweet opinion written prior to the earnings announcement and the abnormal stock price reactions to the earnings announcements (second research question). Furthermore, the predicted stock price reaction to aggregate tweet opinion is more pronounced in firms in weaker information environments, i.e., small firms, and firms with low analyst following and less press coverage (third research question). This last finding is expected because the information contained in aggregate individual tweets about firms in weaker information environments is more likely to be relevant for predicting future stock returns. Finally, our results are robust to specifications that consider a variety of control variables including firm size, market–to-book ratio, ownership sophistication, accounting losses, and a fourth quarter indicator.

Overall, the discovery of this study highlights the importance for capital market participants to consider the nature of information in tweets sent by individuals when assessing the future prospects and value of companies. Our study differs from work on companies using Twitter accounts to communicate with investors in that we investigate tweets specific to a company written by individuals that are either (i) not related in any way to the company they are tweeting about, or (ii) even if they are related to the company (e.g., an employee), they are tweeting on their own behalf using their own personal Twitter account, not on behalf of the company, and their affiliation with the company is unknown. We differ from the work on whether investor mood in general predicts the stock market as a whole in that our analysis is at the firm level with a focus on an important corporate event (earnings announcements). We also differ from the work on investor social media activity and the response to earnings news. Unlike this work, which documents a mediating influence of the volume of social media activity on the returns-earnings relationship, our paper focuses on the ability of information gleaned from social media to predict future earnings realizations, as well as the market's upcoming reaction to these earnings. Finally, we also differ from recent work focusing on user generated research reports on portals such as SeekingAlpha, as we focus on the broad sample of tweets on Twitter, that are not subject to any controls for quality or remuneration.

Our paper makes a meaningful and distinct contribution to extant research on the impact of social media on the capital market in two ways. First, our results have important implications for the role Twitter plays in the investing community. While investing may be viewed as a non-cooperative, zero-sum game, our results demonstrate that individuals use Twitter to share information regarding companies' future prospects for their mutual benefit.

Second, our results are important to regulators. Skeptics may argue that individuals exploit social media tools such as Twitter by disseminating misleading and speculative information to investors, and thus call for regulating social media. However, our results show the opposite; the information on Twitter can help investors in their investment decision-making. Thus, Twitter can play a role in making the market more efficient by uncovering additional value-relevant information, especially for firms in weak information environments, and regulatory intervention does not seem warranted.

The rest of the paper is organized as follows. Section II develops our research questions, and outlines the research design. Section III describes the data, and Section IV presents the empirical results. The final section, Section V, summarizes our main findings and conclusions.

2. Research Question and Design

2.1 THE INFORMATIVENESS OF AGGREGATE OPINION IN INDIVIDUAL TWEETS

We test whether opinions of individuals about a firm's prospects tweeted just prior to a quarterly earnings announcement can predict the firm's earnings and the market response to them. As discussed in the introduction, there are many good reasons for why information from Twitter might be or conversely might not be useful for the prediction of firm-level earnings and returns. We elaborate below.

Information on Twitter might be useful for at least the following four reasons. First, Twitter allows one to tap into the "wisdom of the crowds", a concept that goes back over a century and refers to the phenomenon that the aggregation of information provided by many individuals often results in predictions that are better than those made by any single or a few members of the group, or even experts. One classic example from the turn of the 20th century is Sir Francis Galton's surprising finding that the crowd at a county fair accurately predicted the weight of an ox when their individual guesses were averaged. The crowd's average (or median) prediction was closer to the ox's true weight than the estimates of most crowd members, and even closer than any of the separate estimates made by cattle experts.[5] Similarly, trial by jury can be understood as a manifestation of the wisdom of the crowd, especially when compared to trial by a judge, the single expert.[6] Second, information derived from Twitter comes from a diverse set of information providers. The value of diversity in decision-making has also long been acknowledged. Hong and Page (2004) show analytically that a diverse group of decision makers reaches reliably better

[5] Sir Francis Galton (February 16, 1822 – January 17, 1911) was an inventor, statistician, and investigator of the human mind.

[6] Numerous case studies and anecdotes from economics to illustrate the *Wisdom of Crowds* concept are presented in a book published in 2004 by James Surowiecki, entitled "The Wisdom of Crowds: Why the Many Are Smarter Than the Few and How Collective Wisdom Shapes Business, Economies, Societies and Nations."

decisions than a less diverse group of individuals with superior skills. Moldoveanu and Martin (2010), who refer to this result as the Hong-Page theorem, conclude, "a collection of heterogeneous problem solvers will always beat out a single, expert problem solver."[7] Third, as Twitter represents the opinion of ordinary individuals, this information is unlikely to be tainted by the well documented biases and conflicts of interest that plague information from the traditional intermediaries such as financial analysts. Finally, Twitter has been documented as one of the most timely and efficient sources of information about breaking news events (Osborne and Dredze 2014).

Countering these four reasons are the facts that there are no checks and balances on an open platform such as Twitter. Anyone can open an account and share their opinion, whether it be false, misguided, incorrect or manipulative. The aggregate information on Twitter pertaining to a given stock might represent noise, or even worse intentionally manipulated misinformation. Hence, whether aggregate information on Twitter is useful or not in the prediction of earnings and returns is an empirical question.

2.2 Aggregate Opinion in Individual Tweets and Earnings Surprises

Our first research question asks: Can the aggregate opinion in individual tweets regarding a firm's prospects, expressed by individuals just prior to its earnings announcement, predict a company's earnings? An implication of the *Wisdom of Crowds* concept and the Hong-Page theorem is that the aggregation of opinions provided in individual tweets may result in a more accurate estimate of the forthcoming earnings than the one formed based on analysts. This may be the case because individual tweets reflect opinions of a *large* and *diverse* group of people making *independent* assessments of a company's future prospects. If either of these conditions is

[7] The Hong-Page theorem is discussed in the book "Diaminds" by Moldoveanu and Martin (2010), pp. 163-164.

not met, however, the group may make less accurate earnings forecasts, as small-group judgments tend to be more volatile and extreme, and there is a greater chance that the forecasts will drift towards a misplaced bias. This seems to be the case with financial analysts, who belong to a rather small homogenous group that tend to herd (see, e.g., Welch 2000, Hong et al. 2000), and thus, perhaps not surprisingly, produce inefficient earnings forecasts (see, e.g., Abarbanell 1991, Abarbanell and Bernard 1992, Stevens and Williams 2004). To test our first research question, we estimate the following model:

$$SURP_{i,q} = \alpha + \beta_1 * OPI_{i,q,[-10;-2]} + \beta_2 * SIZE_{i,q} + \beta_3 * MB_{i,q} + \beta_4 * ANL_{i,q} + \beta_5 * INST_{i,q} + \beta_6 * Q4_{i,q} + \beta_7 * LOSS_{i,q-1} + \varepsilon_{i,q} \quad (1)$$

where, the dependent variable, $SURP_{i,q}$, is the market earnings surprise for firm i in quarter q (discussed below in detail). The test variable $OPI_{i,q,[-10;-2]}$, is the aggregate information about firm i in quarter q extracted from individual tweets written in the period -10 to -2, where day 0 is the firm's earnings announcement date (more details below). *SIZE* (firm size), *MB* (market-to-book ratio), *ANL* (number of analysts in the consensus IBES quarterly earnings forecast), *INST* (institutional investor holding), *Q4* (indicator variable for the fourth fiscal quarter), and *LOSS* (indicator variable for past quarterly loss) are six control variables defined in detail in Appendix I. These variables are used to control for effects shown by prior research to explain the cross sectional variation in earnings surprises. In Equation (1), the prediction that the aggregate opinion in tweets predicts earnings, or more specifically the market earnings surprise, implies $\beta_1 > 0$.

One challenge underlying our research design is to estimate the test variable, *OPI*. Along the lines of prior research, we use textual analysis to quantify the opinion expressed in individual tweets. Since performing textual analysis using any word classification scheme is inherently imprecise (see, e.g., Loughran and McDonald 2011), we measure *OPI* by using four alternative methodologies. The first methodology considers both negative and positive words, the next two methodologies consider only negative words, and the fourth methodology is the result of a factor analysis using the first three methodologies as inputs.[8] Our primary focus is on negative word lists because results in prior research indicate that negative word classifications can be effective in measuring tone, as reflected by significant correlations with other financial variables (e.g., Tetlock 2007, Engelberg 2008, Li 2008).

Our first measure, *OPI1*, is based on the enhanced Naïve Bayes classifier developed by Narayanan et al. (2013). It first classifies each tweet, written during the nine-trading-day window [-10;-2], into either positive, negative, or neutral, and computes its reliability (i.e., confidence level ranges from 0 to 100). Then, each tweet is weighted by its confidence level. Finally, *OPI1* is the difference between the weighted number of positive and negative tweets, scaled by *SIZE*. Our second measure, *OPI2*, is defined as minus one multiplied by the total number of words classified as negative during the nine-day window [-10;-2], scaled by *SIZE*, using the negative word list developed by Loughran and McDonald (2011), excluding words with negations. Chen et al. (2014) also use a similar approach in their analysis of reports on SeekingAlpha. The third measure, *OPI3*, is defined as minus one multiplied by the total number of words classified as negative during the nine-day window [-10;-2], scaled by *SIZE*, using the negative category of the Harvard IV-4 word list with inflections and excluding words with negations. Our fourth and final measure, *OPIFACT*, concerns the use of a single factor derived from a factor analysis using *OPI1*, *OPI2*, and *OPI3* as inputs.

Following the standard in the literature, we estimate the dependent variable, *SURP*, using two alternative measures. The first, the standardized unexpected earnings, *SUE*, relies on Compustat data and is measured using quarterly diluted earnings per share excluding extraordinary

[8] Appendix II describes in detail the four measures of aggregate opinion in individual tweets used in this study, and provides examples of tweet classifications for each measure.

items, and applying a seasonal random walk with drift model. This measure of *SURP* is bias free and has been widely used in the literature (e.g., Bernard and Thomas 1990, Ball and Bartov 1996). The second measure of *SURP*, denoted *FE*, is based on analyst quarterly earnings forecasts. Specifically, *FE* is the I/B/E/S reported quarterly earnings per share less the latest I/B/E/S consensus analyst quarterly earnings per share forecast just prior to the earnings announcement date, scaled by the stock price as of the forecast date, multiplied by 100 (see, e.g., Ng et al. 2008).

2.3 Aggregate Opinion in Individual Tweets and market Reaction to Earnings

Our second research question examines the relation between the aggregate opinion in individual tweets just prior to the earnings announcement, and the market response to earnings. To that end, we estimate the following model:

$$EXRET_{i,q,[-1;+1]} = \alpha + \beta_1 * OPI_{i,q,[-10;-2]} + \beta_2 * ANL_{i,q} + \beta_3 * INST_{i,q} + \beta_4 * Q4_{i,q} + \beta_5 * LOSS_{i,q-1} + \varepsilon_{i,q} \quad (2)$$

where, the dependent variable, $EXRET_{i,q,[-1;+1]}$, is buy-and-hold abnormal returns for firm *i*, measured using Carhart's (1997) four factor model for the three-day window, [-1; +1], around the earnings announcement date in quarter *q*, multiplied by 100. We measure buy-and-hold abnormal returns, for firm *i* over *n* trading days, as follows:

$$\prod_t (1 + R_{it}) - \prod_t (1 + ER_{it}) \quad (3)$$

where, R_{it} is the daily return for firm *i* on day *t* (t = -1, 0, +1), inclusive of dividends and other distributions, and ER_{it} is the expected return on day *t* for that firm. If a firm delists during the return accumulation window, we compute the remaining return by using the CRSP daily delisting return, reinvesting any remaining proceeds in the appropriate benchmark portfolio, and adjusting the corresponding market return to reflect the effect of the delisting return on our measures of expected returns (see Shumway 1997, Beaver et al. 2007).[9]

Along the lines of prior research (e.g., Ogneva and Subramanyam 2007), we compute the daily abnormal returns using the Carhart's (1997) four factor model by first estimating the following model using a 40-trading-day hold-out period, starting 55 trading days prior to the earnings announcement date:

$$R_{it} - RF_t = a_i + b_i(RMRF_t) + s_i(SMB_t) + h_i(HML_t) + p_i(UMD_t) + e_{it} \tag{4}$$

where, R_{it} is defined as before, RF_t is the one-month T-bill daily return, $RMRF_t$ is the daily excess return on a value-weighted aggregate equity market proxy, SMB_t is the return on a zero-investment factor mimicking portfolio for size, HML_t is the return on a zero-investment factor mimicking portfolio for book-to-market value of equity, and UMD_t is the return on a zero-investment factor mimicking portfolio for momentum factor.[10]

We then use the estimated slope coefficients from Equation (4), b_i, s_i, h_i, and p_i, to compute the expected return for firm i on day t as follows:

$$ER_{it} = RF_t + b_i(RMRF_t) + s_i(SMB_t) + h_i(HML_t) + p_i(UMD_t) \tag{5}$$

Next, $OPI_{i,q,[-10;-2]}$, the test variable in Equation (2), captures the aggregate information about firm i in quarter q extracted from individual tweets written in days -10 to -2, is measured using four alternative methodologies described above. The four control variables, *ANL* (number of analysts in the consensus IBES quarterly earnings forecast), *INST* (institutional investor

[9] Poor performance-related delistings (delisting codes 500 and 520–584) often have missing delisting returns in the CRSP database (Shumway 1997). To correct for this bias, we set missing performance-related delisting returns to –100 percent as recommended by Shumway (1997). Overall, the percentage of delisting sample firms is small (approximately 0.8 percent and 2 percent for the 60-day and 120-day return windows, respectively), which is not surprising given our relatively short return windows. Still, we replicate our tests excluding delisting returns. The results, not tabulated for parsimony, are indistinguishable from the tabulated results.

[10] *RF*, *RMRF*, *SMB*, *HML*, and *UMD* are obtained from Professor Kenneth French's web site (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html).

holding), *Q4* (indicator variable for the fourth fiscal quarter), and *LOSS* (indicator variable for past quarterly loss) are defined in Appendix I. These variables are used to control for effects shown by prior research to explain the cross section variation in stock returns around earnings announcements.

In Equation (2), the prediction that the aggregate information in individual tweets predicts the stock price reaction to earnings announcements implies $\beta_1 > 0$. This may be the case if, as often argued in the literature, the market relies on analyst earnings forecasts and stock recommendations in forming its earnings expectations and stock prices. It is arguable, however, that the marginal investor who sets the stock price is a sophisticated investor whose earnings expectations and equity valuations may not solely rely on analyst forecasts and recommendations. To assess this possibility, we use *INST* as a control variable.

2.4 Information Environment and the Relationship between Aggregate Opinion in Tweets and Stock Returns

Our third and final research question examines the impact of the information environment on the relation between aggregate opinion in individual tweets and future stock returns. For firms in strong information environments, it is plausible that the information provided by individual tweets is already known to the capital market through such information channels as media releases, press coverage, and analyst reports. Hence, the incremental information content of the aggregate twitter opinion may be low. Conversely, for firms in weak information environments, where information asymmetry among market participants may be substantial, the aggregate twitter opinion may provide incremental information to the capital market.

We use two proxies for information environment. The first is firm size, as small firms have weaker information environments with less publicly available information. For example, Piotroski (2000) shows that among value firms (firms with high book-to-market ratios), small firms are more likely to be "forgotten" and consequently mispriced. Similarly, Mohanram (2005) shows evidence consistent with greater mispricing of small firms among growth firms (firms with low book-to-market ratios). The second proxy is analyst following, a measure of the extent to which earnings and stock-price information reaching the capital market from an important financial intermediary specialized in analyzing and communicating financial information.

We test our third research question by running Equation (2) in partitions, based on each of the two information environment proxies discussed above. We then test for the statistical significance of the difference in β_1 across the partitions and expect β_1 to be significantly greater for the partitions with weaker information environment (i.e., smaller firms and firms with lower levels of analyst following).

3. Sample Selection and Data

3.1 SAMPLE SELECTION

We obtain complete historical Twitter data from GNIP, the first authorized reseller of Twitter data. The data consist of the full archive of Twitter data with stock symbols preceded by cash tags (e.g., $AAPL for Apple Inc., or $PEP for Pepsico Inc.). Focusing on tweets with stock symbols preceded by cash tags increases confidence that the tweets relate to the firm financial performance and value, thereby increasing the reliability of our measures.

Table 1 presents the effects of our sample selection process on the sample size. Our initial sample contains 10,894,037 tweets (66,290 firm-quarters from 4,733 unique firms) for Russell 3000 firms. Dropping tweets containing multiple stock symbols reduces the sample to 8,713,182 tweet (61,357 firm-quarters from 4,668 unique firms). We restrict our sample to tweets pertaining only to a single stock symbol to ensure what stock the tweet is referring to. Next, we require that the firm being tweeted about is on Compustat. This requirement further decreases our sample size to 8,674,195 tweets (60,638 firm-quarters from 4,596 unique firms). We then exclude tweets written prior to December 17, 2008 (i.e., ten trading days before January 1, 2009), due to limited Twitter activity and limited use of the cash tag in Twitter prior to 2009. This requirement further reduces the sample to 8,462,761 tweets (54,906 firm-quarters from 4,132 unique firms). Finally, given that our interest is in the predictive ability of tweets written just prior to the earnings release, we eliminate all tweets written outside of our event window, day -10 to day -2. This last requirement results, as expected, in the largest loss of sample observations by far (more than 7 million tweets). Still, our final sample is broad and consists of 998,495 tweets, covering 34,040 firm-quarters from 3,662 distinct Russell 3000 firms.[11]

3.2 Distribution of Twitter Activity Over Time and Across Industry

Table 2 presents frequency distributions by calendar quarter (Panel A) and industry (Panel B) of tweets and firm-quarters in our final sample.[12] The data in Panel A indicate there has been a dramatic increase in twitter activity over our sample period. In fact, in our sample the number of tweets per calendar quarter increases more than tenfold from 3,580 tweets in the first quarter of 2009 to 141,025 tweets in the fourth quarter of 2012. This pattern is to be expected; it reflects the increased popularity of social media during our sample period. Likewise, the number of firm-quarters in our sample also increases substantially, from 569 in the first quarter of 2009 to 3,126 in the fourth quarter of 2012.

Panel B of Table 2 presents the industry distribution of tweets and firm-quarters in our sample, using the Fama-French 48 industry groupings. For comparison, the industry distribution

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[11] The sample sizes for the tests reported in Tables 4-6 are (slightly) smaller and vary from 32,418 to 30,181 firm-quarters due to additional data requirements.

[12] The tweet activity intervals in Panel A relate to the earnings announcement dates. The tweets are written in the period day -10 to day -2. For example, tweets written between December 17, 2008 and March 17 are included in the calendar quarter "2009, Jan-Mar."

of the Compustat universe is also provided. Generally, our sample spans all 48 industries and its distribution across industries is similar to that of Compustat. Thus, there is little evidence of industry clustering within our sample. Still, it appears that the Computer industry (Group 35 that includes most of the high technology firms and firms in "new economy" industries) draws special attention from tweeters. While this group represents only 3.38 percent of our firm-quarters and 2.84 percent of the Compustat universe, the number of tweets related to stocks in this group (141,938) represents 14.22 percent of all tweets in our sample (998,495). To address a problem arising from a potential clustering tendency within the sample, we use cluster-robust standard error estimators when estimating Equations (1) and (2).

3.3 Descriptive Statistics for the Analysis Variables

Panel A of Table 3 presents the descriptive statistics for the analysis variables. Of the four aggregate opinion variables, *OPI1*, the only measure capturing a net positive opinion, appears to show negative skewness with a zero median, but a negative mean (-0.180), and more extreme distributions on the negative side (P1 = -5.546 whereas P99 = 2.513). This might suggest a "bad-news" bias in tweeting intensity, with investors more likely to share their pessimism on social media rather than their optimism. Our two earnings surprise variables, standardized unexpected earnings (*SUE*) and analyst forecast error (*FE*), appear to differ slightly, with *SUE* having a negative mean (-0.150) and median (-0.012), while *FE* has a negative mean (-0.001) but positive median (0.067). Our measure of excess stock returns around earnings announcements, *EXRET*, has a small positive mean (0.009 percent) and negative median (-0.023 percent).

The firm size variables (*ASSETS* and *MVE*) suggest that the sample spans firms of all sizes, small, medium, and large. The mean market-to-book ratio (*MB*) is 3.061, suggesting that the sample includes many "growth" and intangible intensive firms. The sample also consists of firms in relatively strong information environments. The mean analyst following (*ANL*) is 1.898, which corresponds to an average of over five analysts, and even the first quartile of *ANL* in the sample (1.386) corresponds to close to three analysts. The mean number of press articles (*PRESS*) about each company in the window [-10;-2] using the RavenPack News Analytics database, which includes all news items disseminated via Dow Jones Newswires, is approximately 25. The mean firm has 63.5 percent of its shares held by institutional investors. Finally, slightly less than a quarter of our sample (22.8 percent) corresponds to earnings announcements of fourth quarter results (*Q4*), while slightly more than a quarter of our sample (26.6 percent) reports a quarterly loss in the previous quarter.

3.4 CORRELATION COEFFICIENTS

We turn our attention next to Panel B of Table 3 that presents the pair-wise correlation coefficients among our analysis variables. Figures above and below the diagonal represent, respectively, Spearman and Pearson correlations. The variables include the three measures of aggregate opinion (*OPI1*, *OPI2*, and *OPI3*), the combine aggregate opinion factor (*OPIFACT*), Carthart four-factor adjusted excess returns around earnings announcements (*EXRET*), earnings surprise (*SUE*), forecast error (*FE*) and the control variables.

The three opinion measures show positive correlations with each other, and particularly, the two lexicon based variables (*OPI2* and *OPI3*) show strong correlations with each other (0.68 Spearman; 0.91 Pearson). By construction, the composite factor variable *OPIFACT* is strongly correlated with all three of the underlying opinion variables.

Consistent with expectations, all four opinion variables, our test variables, show positive correlations with our dependent variables, *SUE*, *FE*, and *EXRET*. This may be viewed as *prima facie* evidence of the predictive ability of the aggregate opinion from individual tweets regarding the firm's future earnings and returns.

Also, as one would expect, both *SUE* and *FE* show positive correlations with each other, as well as with *EXRET*. We also examine the correlations between the opinion variables and the control variables. All the opinion variables are negatively correlated with size, analyst following, and press coverage. However, all but one opinion variable are positively correlated with institutional ownership. In addition, all four opinion variables show weak negative correlations with *LOSS*. Finally, the relatively small pairwise correlation coefficients among our control variables indicate there is little evidence of a multi-collinearity problem in our data.

4. Results

4.1 AGGREGATE OPINION IN INDIVIDUAL TWEETS AND EARNINGS SURPRISES

Our first research question pertains to the ability of social media to predict quarterly earnings. Is it possible to predict a company's earnings based on the opinion aggregated from individual tweets regarding the firm in the pre-earnings announcement period? To answer this question, we perform regression tests, where the aggregate opinion from individual tweets is the independent (test) variable, as specified in Equation (1). We estimate the regression using four alternative specifications, the three underlying aggregate opinion variables (*OPI1*, *OPI2*, and *OPI3*) as well as a composite factor (*OPIFACT*), and clustering standard errors by firm.[13] In addition, we use two alternative measures to calibrate the earnings surprise (*SURP*), the dependent variable. The first is the standardized unexpected earnings (*SUE*), and the second is analyst forecast error (*FE*). The results are displayed in Table 4.

Panel A of Table 4 presents the results from estimating Equation (1), where the dependent variable is *SUE*. Model I reports the results using the first measure of aggregate opinion (*OPI1*)

[13] Along the line of prior research (e.g., Petersen 2009), in Table 4 we cluster the standard errors by firm because the errors when SUE and FE are the dependent variables may be correlated over time at the firm level. Conversely, in Tables 5 and Table 6, we cluster the standard errors by calendar quarter and industry because the errors may be correlated in the same calendar period across firms.

from Narayanan et al. (2013). As the results show, *OPI1* loads significantly, with a coefficient of 0.1231 (*t*-statistic = 5.56). Model II reports the results using the second definition of aggregate Twitter opinion (*OPI2*) from Loughran and McDonald (2011). Here too, *OPI2* loads significantly, with a coefficient of 0.1078 (*t*-statistic = 2.93). Model III reports the results for the third definition of Twitter opinion (*OPI3*) using the approach from Tetlock (2007) based on the Harvard psychological dictionary. For Model III as well, *OPI3* loads significantly, with a coefficient of 0.0247 (*t*-statistic = 2.71). Finally, in Model IV, the composite factor *OPIFACT* also loads significantly with a coefficient of 0.5037 (*t*-statistic = 4.07). Taken together, the results provide consistent support that aggregate opinion from individual tweets predicts earnings surprises.

Panel B of Table 4 presents the results from estimating Equation (1) using *FE* as the dependent variable. Given the need for analyst following data, there is a slight (under 7 percent) decline in sample size. The results are broadly similar to those in Panel A. In Model I, the coefficient on *OPI1* is positive (0.0145) and significant (*t*-statistic = 2.07). Likewise, in Model II, the coefficient on *OPI2* is also positive (0.0273) and significant (*t*-statistic = 2.23). In Model III, we continue to find a significant relationship between forecast error and aggregate Twitter opinion, as the coefficient on *OPI3* is significantly positive (0.0054, *t*-statistic = 1.93). Finally, Model IV confirms that this relationship is significant when we use the composite factor *OPIFACT* (0.1070, *t*-statistic = 2.68).

To summarize, the results in Table 4 suggest that aggregate opinion from individual Tweets help predict future earnings realizations. This finding is robust to the definition of both our test variable and the dependent variable, as well as to the inclusion of a multitude of control variables. It supports the *Wisdom of Crowds* and the value of diversity concepts discussed earlier.

4.2 AGGREGATE OPINION IN INDIVIDUAL TWEETS AND ABNORMAL STOCK RETURNS AROUND EARNINGS ANNOUNCEMENTS

We now turn our attention to our second research question: Can investors profit from the signals extracted from the aggregate opinion in social media? To test this question, we examine the association between abnormal stock returns around earnings announcements and the aggregate Twitter opinion in a nine-day period leading to the earnings announcement, -10 to -2. We measure abnormal stock returns (*EXRET*) as the buy-and-hold returns for the three-day window around earnings announcements -1 to +1, controlling for the four factors from the Carhart (1997) model, which uses the three Fama-French factors (market-premium factor, R_m-R_f, size factor, *SMB*, and book-to-market factor, *HML*) as well as momentum (*UMD*). The regressions are estimated with all four alternative measures of aggregate Twitter opinion and using standard errors clustered by calendar quarter and industry.[14] The results are presented in Table 5.

Model I presents the results using *OPI1* as the opinion variable. The results suggest a positive relationship between aggregate Twitter opinion and abnormal returns, as the coefficient on *OPI1* is significant and positive (0.1680, *t*-statistic = 4.04). This relationship holds with alternate measures of opinion. For Model II, the coefficient on *OPI2* is significant and positive (0.3449, *t*-statistic = 7.48). For Model III, the coefficient on *OPI3* is also significantly positive (0.0997, *t*-statistic = 6.92). Finally, Model IV confirms that this relationship is robust to the use of the composite factor *OPIFACT* (1.4482, *t*-statistic = 9.09).

The results of Table 5 hence suggest a robust relationship between aggregate opinion from individual tweets and future stock returns around earnings announcements. This builds on the results from Table 4, as it suggests that not only is there the *Wisdom of Crowds* and the value of diversity effect in our data, but investors can actually benefit from this. To what extent can

[14] As the excess return variable, *EXRET*, already includes controls for size and book-to-market, we do not include these variables as independent variables. Results are unchanged when we include these as additional control variables.

investors benefit from the information in tweets? The economic significance of the estimated coefficient may be illustrated as follows. The inter-quartile range of *OPI1* is 0.392 (= 0.147 – -0.245). A coefficient of 0.1680 implies a difference in *EXRET*, the abnormal return around earnings announcements, of 0.066 percent (=0.1680*0.392) per three trading days (or approximately 5 percent annualized return). Using the composite factor *OPIFACT*, the difference in EXRET is nearly twice as high, 0.113 percent (=1.4482*(0.133 – 0.055)).

4.3 When does Aggregate Twitter Opinion Matter More : The Impact of Information Environment

The results thus far suggest that aggregate opinion from individual tweets provide valuable information that can help predict future earnings realizations as well as abnormal stock returns around earnings announcements. However, this effect is unlikely to be uniform. Firms in strong information environments are likely to have numerous alternative sources of information, and it is possible that the information shared by individuals on Twitter has already been conveyed to the market through other sources. Hence, this information is likely to be less relevant for predicting returns. On the other hand, for firms in weak information environments, it is more likely that at least part of the information contained in aggregate twitter opinion has not reached the market yet, and is hence more relevant for predicting returns. We examine this conjecture next.

We use three alternative proxies for the information environment—firm size, analyst following, and press coverage—which, as shown in Panel B of Table 3 above, are highly correlated. We divide the sample into equal size groups per calendar quarter on the basis of each of these variables, and then rerun the analysis of Table 5. The results are presented in Table 6.

We first partition our sample based on size into two equal sized groups. We then re-estimate Equation (2) across the two subsamples, and test whether the relationship between our opinion (test) variables and *EXRET* is indeed stronger for smaller firms. The results are presented in Panel A of Table 6. The first two columns present the regression results using *OPI1* as the independent variable of interest. For both small and large firms, we see a significant relationship between *OPI1* and *EXRET*, with a coefficient of 0.383 (*t*-statistic = 3.68) for small firms and a smaller and insignificant coefficient of 0.061 (*t*-statistic = 1.60) for large firms. Further, as we hypothesize, the relationship between *OPI1* and *EXRET* is indeed stronger for small firms than large firms. The difference between the coefficients on *OPI1* (SMALL minus LARGE) is positive 0.321 and significant (*t*-statistic = 2.90). Similar significant differences are found for the three other alternative measures of the aggregate opinion in Twitter, *OPI2*, *OPI3*, and *OPIFACT*. This suggests that aggregate Twitter opinion does indeed matter more for predicting abnormal stock returns around earnings announcements for smaller firms than for larger firms.

We next partition our sample into two equal sized groups on the basis of analyst following. As before, we rerun the return Equation (2) across the two subsamples, and test whether the relationship between our opinion variables and *EXRET* is indeed stronger for firms with lower analyst following. The results are presented in Panel B of Table 6.

The first two columns present the regressions using *OPI1* as the independent variable of interest. For both low and high analyst following firms, we see a significant relationship between *OPI1* and *EXRET*, with a coefficient of 0.187 (*t*-statistic = 2.08) for low analyst following firms and a coefficient of 0.150 (*t*-statistic = 4.23) for high analyst following firms. However, the relationship between *OPI1* and *EXRET* is not significantly stronger for firms with lower analyst following, as the difference between the coefficients on *OPI1* is small, 0.037, and insignificant (*t*-statistic = 0.38). The next set of columns present the results for *OPI2*. For this specification, we do find a significantly stronger relationship between *OPI2* and *EXRET* for firms with lower analyst following as compared to firms with higher analyst following. Specifically, the coefficient of *OPI2* for the low analyst following subsample is positive, 0.600, and significant (*t*-statistic = 6.88), whereas the coefficient for the high analyst following subsample is 0.228 (*t*-statistic = 3.69). The difference in the coefficients on *OPI2*, 0.372 is significant (*t*-statistic =3.48). Similar significant differences are found for *OPI3* and *OPIFACT*. This suggests that the aggregate twitter opinion does indeed matter more for predicting stock returns around earnings announcements for firms with lower levels of analyst following.

Finally, we partition our sample into two equal sized groups on the basis of press coverage. We obtain press coverage data from the RavenPack News Analytics database, which provides time-stamped data for all news items disseminated via Dow Jones Newswires. We create a measure of press coverage by counting the number of press articles about each company in the window [-10;-2], concurrent to when we measure *OPI*.[15] We rank observations into low and high press coverage subsamples by calendar quarter (similar to *SIZE* and *ANL*). As before, we rerun Equation (2) across the two subsamples, and test whether the relationship between our opinion variables and *EXRET* is indeed stronger for firms in the low press coverage group. The results, presented in Panel C of Table 6, are consistent with the results in Panels A and B. Specifically, all of our *OPI* variables significantly predict *EXRET* in both the low and high press coverage subsamples (except *OPI1* in the high press coverage firms where the relation is positive yet statistically insignificant). More importantly, the positive relation between *OPI* and *EXRET* is significantly stronger for firms with low press coverage than firms with high press coverage (except for *OPI3* where the difference is positive yet insignificant). The results in Panel C suggest that the aggregate Twitter opinion plays a greater role at predicting stock returns around earnings announcements for firms with lower levels of press coverage.

In summary, the findings in Table 6 suggest that for firms in weak information

[15] The results are similar if alternatively we use press coverage for days [-41;-11], period just prior to the measurement window for *OPI*.

environments the aggregate individual opinion in Twitter is as expected more relevant for predicting stock returns around earnings announcements.

5. Conclusions

The past few years have seen a dramatic increase in the use of social media. This phenomenon has also had an impact on the capital market. Firms use social media as a means of communication to their investor base. Increasingly, individual investors use social media to share their information and insights about the prospects of firms and stocks. Social media platforms, such as Twitter, have transformed the capital market in two significant ways. From the firms' perspective, social media is now an important channel through which firms can communicate with investors in a timely, cost effective, and intensive manner. From the investors' perspective, social media provides access to information, not just from the firms, but also from each other.

Ex-ante, it is unclear whether the information generated and disseminated by individuals in social media platforms, such as Twitter, will be value relevant. On one hand, there is considerable anecdotal and empirical evidence consistent with the *Wisdom of Crowds* concept and the Hong-Page Theorem (i.e., the value of diversity concept), suggesting information in Twitter provided by individuals may have value. On the other hand, given that such platforms are completely unregulated, the information may be speculative, dubious, and perhaps even manipulated.

In this paper, we examine whether social media platforms such as Twitter provide value-relevant information to the market. Specifically, we test whether the aggregate opinion in individual tweets about a firm can help predict the firm's earnings and stock returns around earnings announcements, and whether the ability to predict abnormal returns is greater for firms in weaker information environments. To that end, we analyze a broad sample of 998,495 tweets (covering 34,040 firm-quarters from 3,662 distinct Russell 3000 firms) by individuals opining on a firm's future prospects in the nine-trading-day period leading up to the firms' quarterly earnings announcements. The sample spans the four-year period, January 1, 2009 to December 31, 2012. We use three distinct approaches to create measures of aggregate investor opinion derived from individual tweets (*OPI1*, *OPI2*, and *OPI3*), as well as a composite measure that combines the three approaches using factor analysis (*OPIFACT*).

We find that the aggregate information in individual tweets help predict quarterly earnings. Controlling for other determinants of earnings, we find a strong positive association between aggregate investor opinion written prior to the earnings announcement and the ensuing market earnings surprise for all four measures. This is consistent with the *Wisdom of Crowds* concept and the Hong-Page theorem, as individuals' tweets predict earnings more accurately than analysts (experts) do. Further, we also find that aggregate investor opinion predicts abnormal returns around earnings announcements, i.e., investors can potentially profit from the information in aggregate investor opinion, as this information does not appear to already be impounded in stock prices. Finally, the relationship between the aggregate information in tweets and abnormal returns is strongest for firms in the weakest information environments, such as small firms and firms with lower levels of analyst following. This suggests that social media can be a particularly valuable conduit of information for firms in weak information environments.

The contribution of this paper is twofold. First, our results have important implications for the role social media plays in the investing community. While investing may be viewed as a non-cooperative, zero-sum game, our results demonstrate that individuals use social media to share information regarding companies' future prospects for their mutual benefit.

Second, our results are important to regulators. Skeptics may argue that individuals exploit social media by disseminating misleading and speculative information to investors, and thus call for regulating social media. However, our results show the opposite; the information in social media may help investors in their investment decision-making. Thus, social media can play a role in making the market more efficient by uncovering additional value-relevant information, especially for firms in weak information environments, and regulatory intervention does not seem warranted.

References

ABARBANELL, J. 'Do analysts' earnings forecasts incorporate information in prior stock price changes?' *Journal of Accounting and Economics* 14 (1991): 147–165.

ABARBANELL, J. and V. BERNARD 'Tests of analysts' overreaction/underreaction to earnings information as an explanation for anomalous stock price behavior.' *Journal of Finance* 47 (1992): 1181–1207.

ANTWEILER, W. and M. FRANK. 'Is all that talk just noise? The information content of Internet stock message boards.' *Journal of Finance* 59 (2004): 1259–1294.

BALL, R. and E. BARTOV. 'How naïve is the stock market's use of earnings information?' *Journal of Accounting and Economics* 21 (1996); 319–337.

BEAVER, W., M. McNICHOLS and R. PRICE. 'Delisting returns and their effect on accounting-based market anomalies.' *Journal of Accounting and Economics* 43 (2007): 341–368.

BERNARD, V., and J. THOMAS. 'Evidence that stock prices do not fully reflect the implications of current earnings for future earnings.' *Journal of Accounting and Economics* 13 (1990): 305–340.

BLANKESPOOR, E., G. MILLER and H. WHITE. 'The role of dissemination in market liquidity: Evidence from firms' use of Twitter™'. *The Accounting Review* 89 (2014): 79–112.

BOLLEN, J., H. MAO and X. ZHENG. 'Twitter mood predicts the stock market.' *Journal of Computational Science* 2 (2011): 1–8.

BROWN, L. 'Forecast selection when all forecasts are not equally recent.' *International Journal of Forecasting* 7 (1991): 349–356.

CARHART, M. 'On persistence in mutual fund performance.' *Journal of Finance* 52 (1997): 57–82.

CHEN, H., P. DE, Y. HU and B. HWANG. 'Wisdom of crowds: The value of stock opinions transmitted through social media.' *Review of Financial Studies* 27 (2014): 1367–1403.

COHEN, L, A. FRAZZINI and C. MALLOY. 'Sell-side school ties.' *Journal of Finance* 65 (2010): 1409-1437.

CURTIS, A., V. RICHARDSON and R. SCHMARDEBECK 'Investor attention and the pricing of earnings news.' Unpublished paper, University of Washington, 2014. Available at http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2467243.

DUGAR, A. and S. NATHAN. 'The effect of investment banking relationships on financial analysts' earnings forecasts and investment recommendations.' *Contemporary Accounting Research* 12 (1995): 131–160.

ENGLEBERG, J. Costly information processing: Evidence from earnings announcements. Unpublished paper, University of California San Diego, 2008. Available at http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1107998

HONG, H., J. KUBIK and A. SOLOMON. 'Security analysts' career concerns and herding of earnings forecasts.' *Rand Journal of Economics* 31 (2000): 121–144.

HONG, L. and S. PAGE. 'Groups of diverse problem solvers can outperform groups of high-ability problem solvers' *Proceedings of the National Academy of Science* 101-46 (2004): 16385–16389.

JEGADEESH, N. and W. KIM. 'Do analysts herd? An analysis of recommendations and market reactions.' *Review of Financial Studies* 23 (2010): 901-937.

JUNG, M., J. NAUGHTON, A. TAHOUN and C. WANG. 'Corporate use of social media'. Unpublished paper, New York University, 2015. Available at http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2588081

LEE, F., A. HUTTON and S. SHU. 'The Role of Social Media in the Capital Market: Evidence from Consumer Product Recalls." *Journal of Accounting Research* 53-2 (2015): 367-404.

LI, F 'Annual report readability, current earnings, and earnings persistence'. *Journal of Accounting and Economics* 45 (2008): 221–247.

LIN, H. and M. McNICHOLS. 'Underwriting relationships, analysts' earnings forecasts and investment recommendations.' *Journal of Accounting and Economics* 25 (1998): 101–127.

LOUGHRAN, T. and B. McDONALD. 'When is a liability not a liability? Textual Analysis, Dictionaries, and 10-Ks.' *Journal of Finance* 66 (2011): 35–65.

MAO, Y., W. WEI, B. WANG, and B. LIU. 'Correlating S&P 500 stocks with twitter data.' *Proceedings of the First ACM International Workshop on Hot Topics on Interdisciplinary Social Networks* (2012), 69–72.

MICHAELY, R. and K. WOMACK. 'Conflict of interest and the credibility of underwriter analyst recommendations.' *Review of Financial Studies* 12 (1999): 653–686.

MOHANRAM, P. 'Separating winners from losers among low book-to-market stocks using financial statement analysis.' *Review of Accounting Studies* 10 (2005): 133–170.

MOLDOVEANU, M. and R. MARTIN, R. Diaminds: Decoding the mental habits of successful thinkers. University of Toronto Press, 2010.

NARAYANAN, V., I. ARORA and A. BHATIA. 'Fast and accurate sentiment classification using an enhanced Naive Bayes model.' *Intelligent Data Engineering and Automated Learning IDEAL 2013. Lecture Notes in Computer Science* 8206 (2013), 194–201.

NG, J., T. RUSTICUS and R. VERDI. 'Implications of transaction costs for the post-earnings announcement drift.' *Journal of Accounting Research* 46 (2008): 661–696.

O'BRIEN, P. and R. BHUSHAN 'Analyst following and institutional ownership'. *Journal of Accounting Research* 28 (1990): 55–76.

OGNEVA, M. and K.R. SUBRAMANYAM. 'Does the stock market underreact to going concern opinions? Evidence from the U.S. and Australia.' *Journal of Accounting and Economics* 43 (2007): 439–462.

OSBORNE, M. and M. DREDZE. 'Facebook, Twitter and Google Plus for breaking news: Is there a winner?' *Proceedings of the Eighth International AAAI Conference on Weblogs and Social Media* (2014), 611–614.

PETERSEN, M. 'Estimating standard errors in finance panel data sets: Comparing approaches.' *Review of Financial Studies* 22 (2009): 435–480.

PIOTROSKI, J. 'Value investing: The use of historical financial statement information to separate winners from losers.' *Journal of Accounting Research* 38 Supplement (2000): 1–41.

SHUMWAY, T. 'The delisting bias in CRSP data.' *Journal of Finance* 52 (1997): 327–340.

STEVENS, D. and A. WILLIAMS. 'Inefficiency in earnings forecasts: Experimental evidence of reactions to positive vs. negative information.' *Experimental Economics* 7 (2004): 75–92.

TETLOCK, P. Giving content to investor sentiment: The role of media in the stock market. *Journal of Finance* 62 (2007): 1139–1168.

WELCH, I. 'Herding among security analysts.' *Journal of Financial Economics* 58 (2000): 369–396.

APPENDIX I
Variable Definitions

Variable	Definition
OPI1	Total number of tweets classified as positive less total number of tweets classified as negative during the trading-day window [-10;-2], where day zero is the quarterly earnings announcement date, scaled by *SIZE*, using an enhanced Naïve Bayes classifier developed by Narayanan et al. (2013). Each positive or negative tweet is weighted by the corresponding confidence level (see description in Appendix II)
OPI2	Minus one multiplied by the total number of words classified as negative during the trading-day window [-10;-2], where day zero is the quarterly earnings announcement date, scaled by *SIZE*, using the negative word list developed by Loughran and McDonald (2011) and excluding words with negations (see description in Appendix II)
OPI3	Minus one multiplied by the total number of words classified as negative during the trading-day window [-10;-2], where day zero is the quarterly earnings announcement date, scaled by *SIZE*, using the negative category of the Harvard IV-4 word list with inflections and excluding words with negations (see description in Appendix II)
OPIFACT	Factor from a factor analysis using *OPI1*, *OPI2*, and *OPI3* (see description in Appendix II)
EXRET (%)	Buy-and-hold abnormal returns measured using Carhart's (1997) four factor model for the window [-1;+1], where day zero is the quarterly earnings announcement date, multiplied by 100
SUE	Standardized unexpected earnings, measured using quarterly diluted earnings per share excluding extraordinary items (*EPSFXQ*) and applying a seasonal random walk with drift model
FE (%)	Analyst earnings forecast error, measured as I/B/E/S reported quarterly earnings per share less the latest I/B/E/S consensus analyst quarterly earnings per share forecast just prior to the quarterly earnings announcement date, scaled by stock price as of the forecast date, multiplied by 100
ASSETS	Total assets (*ATQ*)
MVE	Market value of equity (*CSHOQ*PRCCQ*)
SIZE	Natural logarithm of MVE
MB	Ratio of market value to book value of equity ([*CSHOQ*PRCCQ*]/*CEQQ*)
ANL	Natural logarithm of one plus the number of analysts in the latest I/B/E/S consensus analyst quarterly earnings per share forecast prior to the quarter end date
INST	Number of shares held by institutional investors scaled by total shares outstanding as of the quarter end date
Q4	Indicator variable equal to one if the quarter is the fourth fiscal quarter, zero otherwise
LOSS	Indicator variable equal to one if earnings before extraordinary items (*IBQ*) is strictly negative in the prior quarter, zero otherwise
PRESS	Number of press articles about each company in the window [-10;-2], where day zero is the quarterly earnings announcement date, using the RavenPack News Analytics database, which includes all news items disseminated via Dow Jones Newswires

APPENDIX II
Measuring Opinion in Individual Tweets

We employ four measures to capture the aggregate opinion in individual tweets as described in this appendix.

OPI1

OPI1 is defined as the total number of tweets classified as positive less the total number of tweets classified as negative during the nine-day window [-10;-2], scaled by *SIZE*, where the classification into positive or negative tweets is based on the enhanced Naïve Bayes classifier developed by Narayanan et al. (2013).[16] Each positive or negative tweet is weighted by the corresponding confidence level. The program classifies any type of message (e.g., tweet, review, message from message board, forum, blog, etc.) as positive, neutral, or negative, with a confidence level.

Examples

Tweet	**Result**	**Confidence Level (%)**
$AAPL relatively strong in a big way. Very nice upside action. Looking to buy @ 96.55 limit.	Positive	98.8
Nice gains out of $HERO today. Holding tight looking for new hod. 3% gains so far	Positive	81.9
$GME Aug 21 calls hitting bids on over 3,500 volume, doesn't look very good ahead of earnings on 8/18	Negative	80.0
$JOE can be shorted. Remind me this week to do so...	Negative	64.7

OPI2

OPI2 is defined as minus one multiplied by the total number of words classified as negative during the nine-day window [-10;-2], scaled by *SIZE*, using the negative word list developed by Loughran and McDonald (2011), excluding words with negations. Loughran and McDonald (2011) created several word lists to be used in textual analysis in financial applications.[17]

Examples (emphasis added to show the negative words identified)

Tweet	**Number of Negative Words**
$APOL just now **breaking** but will be choppy. If market goes, this will work. If market falters, watch out. Be aware of your **STOPS** always.	2

[16] A demo of this classifier is available at http://sentiment.vivekn.com/, and the program is available at http://sentiment.vivekn.com/docs/api/.
[17] The word lists developed by Loughran and McDonald (2011) are available at http://www.nd.edu/~mcdonald/Word_Lists.html.

rumor that $IBM to **layoff** 14,000	1
@DelishDish1971 oh that scumbag. Yes, **manipulation**. Again $QCOR being **accused** of " good management" lol Co should **sue**, I would.	3
I think $AAPL (Apple, Inc) will **miss** earnings because the company is doing things that would make #SteveJobs stab himself in the eyes.	1

OPI3

OPI3 is defined as minus one multiplied by the total number of words classified as negative during the nine-day window [-10;-2], scaled by *SIZE*, using the negative category of the Harvard Psychosociological Dictionary, i.e. the Harvard IV-4 TagNeg (H4N) word list, with inflections and excluding words with negations.

Examples (emphasis added to show the negative words identified)

Tweet	Number of Negative Words
I think $amzn is a potential **short**	1
I like $SWI but i **hate** holding through earnings which are in a few days. I'll buy and **try** to **get** out prior to the earnings on 2/7	3
What if $JPM had a derivatives book way **too** big, with big **loses**, with counterparties **too** big to **bail** & **too** big to **fail**? What would you do?	6
selling $cstr puts down here just **trying** to **break even** at 2.15. tiny **loss**.	4

OPIFACT

To isolate the underlying common factor(s) related to aggregate Twitter opinion, we run a factor analysis using the three opinion variables discussed above. The factor analysis indicates that there is only one factor with an eigen value greater than 1, and that the loadings are significant and positive for each of three variables. The loadings are 0.2543 for *OPI1*, 0.9805 for *OPI2*, and 0.9786 for *OPI3*. As there is only a single factor, there is no need for factor rotation. The single factor is calculated after the variables are standardized to have zero mean and unit variance. The weights using the standardized variables are 0.1282, 0.4943, and 0.4933 for *OPI1*, *OPI2*, and *OPI3* respectively.

TABLE 1
Sample Selection

Criterion	Tweets	Firm-Quarter Observations	Unique Firms
Tweets between March 21, 2006 and December 31, 2012 with $ tag followed by ticker symbols of Russell 3000 firms	10,894,037	66,290	4,733
Tweets pertaining to a single stock symbol	8,713,182	61,357	4,668
Availability of data on the Compustat database for the firms mentioned in the tweets	8,674,195	60,638	4,596
Tweets on or after December 17, 2008 (i.e., ten trading days prior to January 1, 2009)	8,462,761	54,906	4,132
Tweets in the nine-trading-day window [-10;-2], where day zero is the quarterly earnings announcement date, and quarterly earnings announcement dates are between January 1, 2009 and December 31, 2012	998,495	34,040	3,662
Final Sample	**998,495**	**34,040**	**3,662**

TABLE 2, PANEL A
Distribution of Tweets per Calendar Quarter

Sample consists of 34,040 firm-quarter observations (3,662 distinct firms), with earnings announcement dates between January 1, 2009 and December 31, 2012.

Calendar Quarter	Tweets		Firm-Quarter Observations	
	N	%	N	%
2009, Jan-Mar	3,580	0.36	569	1.67
2009, Apr-Jun	13,406	1.34	1,110	3.26
2009, Jul-Sept	14,870	1.49	1,233	3.62
2009, Oct-Dec	15,250	1.53	1,305	3.84
2010, Jan-Mar	24,806	2.48	1,686	4.95
2010, Apr-Jun	30,985	3.10	1,851	5.44
2010, Jul-Sept	30,770	3.08	2,089	6.14
2010, Oct-Dec	30,205	3.03	2,125	6.24
2011, Jan-Mar	60,541	6.06	2,690	7.90
2011, Apr-Jun	77,288	7.74	2,676	7.86
2011, Jul-Sept	78,239	7.84	2,670	7.84
2011, Oct-Dec	105,579	10.57	2,572	7.56
2012, Jan-Mar	106,941	10.71	2,539	7.46
2012, Apr-Jun	139,755	14.00	2,682	7.88
2012, Jul-Sept	125,255	12.55	3,117	9.16
2012, Oct-Dec	141,025	14.12	3,126	9.18
All	**998,495**	**100.00**	**34,040**	**100.00**

TABLE 2, PANEL B

Distribution of Tweets per Industry Group based on Fama-French 48-industry classification

Industry Group & Description	Tweets		Firm-Quarters		Compustat
	N	%	N	%	%
1: Agriculture	1,865	0.19	96	0.28	0.38
2: Food Products	15,631	1.57	550	1.62	1.35
3: Candy and Soda	3,407	0.34	87	0.26	0.32
4: Alcoholic Beverages	3,012	0.30	106	0.31	0.26
5: Tobacco Products	1,791	0.18	56	0.16	0.10
6: Recreational Products	1,787	0.18	118	0.35	0.57
7: Entertainment	22,138	2.22	390	1.15	1.26
8: Printing and Publishing	3,117	0.31	184	0.54	0.47
9: Consumer Goods	6,624	0.66	364	1.07	1.07
10: Apparel	10,737	1.08	431	1.27	0.95
11: Healthcare	4,532	0.45	478	1.40	1.29
12: Medical Equipment	13,842	1.39	965	2.83	2.82
13: Pharmaceutical Products	74,066	7.42	2,432	7.14	6.77
14: Chemicals	13,561	1.36	716	2.10	1.82
15: Rubber and Plastic Products	860	0.09	137	0.40	0.49
16: Textiles	456	0.05	62	0.18	0.20
17: Construction Materials	6,138	0.61	389	1.14	1.23
18: Construction	5,675	0.57	416	1.22	0.83
19: Steel Works, Etc.	13,129	1.31	447	1.31	1.09
20: Fabricated Products	1,601	0.16	61	0.18	0.16
21: Machinery	17,842	1.79	996	2.93	2.38
22: Electrical Equipment	6,044	0.61	501	1.47	1.49
23: Automobiles and Trucks	11,289	1.13	466	1.37	1.31
24: Aircraft	3,944	0.39	197	0.58	0.42
25: Shipbuilding, Railroad Equipment	905	0.09	77	0.23	0.16
26: Defense	1,675	0.17	93	0.27	0.16
27: Precious Metals	3,241	0.32	145	0.43	1.53
28: Non-Metallic and Metal Mining	6,223	0.62	219	0.64	1.67
29: Coal	7,414	0.74	153	0.45	0.33
30: Petroleum and Natural Gas	51,039	5.11	1,808	5.31	4.84
31: Utilities	30,304	3.03	1,003	2.95	3.98
32: Communications	22,772	2.28	863	2.54	3.25
33: Personal Services	6,768	0.68	452	1.33	0.99
34: Business Services	126,201	12.64	3,308	9.72	9.95
35: Computers	141,938	14.22	1,152	3.38	2.84
36: Electronic Equipment	43,140	4.32	1,995	5.86	5.54
37: Measuring and Control Equipment	15,026	1.50	531	1.56	1.62
38: Business Supplies	6,018	0.60	379	1.11	0.84
39: Shipping Containers	882	0.09	85	0.25	0.20
40: Transportation	14,882	1.49	935	2.75	2.75
41: Wholesale	8,399	0.84	801	2.35	2.67
42: Retail	74,445	7.46	1,900	5.58	3.48
43: Restaurants, Hotels, Motels	35,176	3.52	541	1.59	1.32
44: Banking	58,537	5.86	2,521	7.41	10.39
45: Insurance	23,486	2.35	1,253	3.68	2.79
46: Real Estate	2,509	0.25	188	0.55	1.08
47: Trading	61,266	6.14	2,555	7.51	6.21
48: Miscellaneous	13,161	1.32	438	1.29	2.38
All Industries	**998,495**	**100.00**	**34,040**	**100.00**	**100.00**

TABLE 3
Descriptive Statistics

The sample consists of 34,040 firm-quarter observations (3,662 distinct firms), with earnings announcement dates between January 1, 2009 and December 31, 2012. See Appendix I for variable definition. To mitigate the influence of outliers, all continuous variables are winsorized at the 1st and 99th percentiles. In Panel B, figures above/below diagonal represent Spearman/Pearson correlation coefficients.

Panel A: Descriptive Statistics

Variable	P1	Q1	Mean	Median	Q3	P99	Std Dev
OPI1	-5.546	-0.245	-0.180	0.000	0.147	2.513	1.018
OPI2	-6.184	-0.182	-0.276	0.000	0.000	0.000	0.829
OPI3	-23.393	-0.951	-1.273	-0.303	0.000	0.000	3.214
OPIFACT	-1.572	0.055	0.037	0.112	0.133	0.214	0.241
SUE	-16.472	-1.671	-0.150	-0.012	1.667	10.165	3.924
FE (in %)	-8.280	-0.095	-0.001	0.067	0.286	4.432	1.337
EXRET (in %)	-24.505	-4.048	0.009	-0.023	3.950	26.154	8.126
ASSETS	24.6	365.9	8,840.7	1,410.0	5,255.4	189,079.0	25,505.8
MVE	34.4	310.1	5,339.6	1,040.7	3,596.6	104,664.2	14,050.6
SIZE	3.538	5.737	7.045	6.948	8.188	11.559	1.723
MB	0.293	1.162	3.061	1.865	3.251	27.611	3.893
ANL	0.000	1.386	1.898	2.079	2.639	3.466	0.949
INST	0.000	0.444	0.635	0.714	0.873	1.000	0.296
Q4	0.000	0.000	0.228	0.000	0.000	1.000	0.419
LOSS	0.000	0.000	0.266	0.000	1.000	1.000	0.442
PRESS	0.000	4.000	24.648	14.000	30.000	235.00	36.210

Panel B: Correlation Matrix

	OPI1	*OPI2*	*OPI3*	*OPIFACT*	*SUE*	*FE*	*EXRET*	*SIZE*	*MB*	*ANL*	*INST*	*Q4*	*LOSS*	*PRESS*
OPI1		0.04	0.14	0.59	0.04	0.02	0.02	0.00	0.01	0.00	0.00	0.05	-0.03	0.03
OPI2	0.15		0.68	0.66	0.02	0.01	0.04	-0.21	-0.14	-0.21	0.02	-0.02	-0.05	-0.18
OPI3	0.22	0.91		0.74	0.04	0.01	0.04	-0.23	-0.13	-0.23	0.01	0.01	-0.05	-0.20
OPIFACT	0.47	0.91	0.94		0.04	0.02	0.04	-0.18	-0.10	-0.18	0.02	0.04	-0.06	-0.14
SUE	0.03	0.02	0.01	0.03		0.26	0.14	0.01	0.03	-0.01	-0.01	0.03	0.02	-0.03
FE	0.01	0.01	0.01	0.01	0.19		0.35	0.01	-0.01	0.02	0.04	-0.02	-0.03	0.01
EXRET	0.02	0.04	0.04	0.05	0.13	0.23		0.02	0.00	0.01	0.03	0.01	-0.03	0.01
SIZE	-0.06	-0.19	-0.20	-0.20	0.01	0.08	0.01		0.25	0.69	0.40	0.01	-0.35	0.34
MB	-0.01	-0.13	-0.12	-0.11	0.01	0.01	-0.01	0.08		0.20	0.11	0.01	-0.06	0.10
ANL	-0.04	-0.12	-0.12	-0.13	-0.01	0.06	0.01	0.64	0.06		0.49	0.02	-0.22	0.38
INST	-0.02	0.04	0.04	0.03	0.00	0.07	0.03	0.38	-0.02	0.58		0.03	-0.22	0.24
Q4	0.04	0.00	0.01	0.02	0.01	-0.02	0.01	0.01	0.00	0.02	0.02		-0.02	0.01
LOSS	0.00	-0.04	-0.04	-0.04	0.02	-0.09	-0.03	-0.35	0.08	-0.22	-0.23	-0.02		-0.09
PRESS	-0.01	-0.39	-0.39	-0.36	-0.03	0.01	0.00	0.41	0.03	0.32	0.15	0.01	-0.08	

TABLE 4, PANEL A
Tweet Opinion and Earnings Surprises at Earnings Announcements

This table (Panels A and B) presents the results from the regressions presented below and estimated using standard errors clustered by firm. The sample consists of 34,040 firm-quarter observations (3,662 distinct firms), with earnings announcement dates between January 1, 2009 and December 31, 2012. *t*-statistics are in parenthesis below coefficient estimates. Coefficient estimates and *t*-statistics are bolded for the variable of interest OPI. ***,**,* represent statistical significance at $p < 0.01$, $p < 0.05$, and $p < 0.10$ (two-tailed), respectively. See Appendix I for variable definitions. To mitigate the influence of outliers, all continuous variables are winsorized at the 1st and 99th percentiles.

Model: $SUE = \alpha + \beta_1 * OPI_{[-10;-2]} + \beta_2 * SIZE + \beta_3 * MB + \beta_4 * ANL + \beta_5 * INST + \beta_6 * Q4 + \beta_7 * LOSS + \varepsilon$

Variable	Expected Sign	Coefficient *(t-statistic)*			
		OPI1	*OPI2*	*OPI3*	*OPIFACT*
		Model I	Model II	Model III	Model IV
Intercept		-0.6648***	-0.6976***	-0.6908***	-0.7788***
		(-6.14)	*(-6.53)*	*(-6.47)*	*(-7.22)*
OPI	+	**0.1231*****	**0.1078*****	**0.0247*****	**0.5037*****
		(5.56)	***(2.93)***	***(2.71)***	***(4.07)***
SIZE		0.0850***	0.0913***	0.0907***	0.0961***
		(4.97)	*(5.41)*	*(5.36)*	*(5.67)*
MB		0.0109*	0.0133**	0.0130**	0.0136**
		(1.71)	*(2.06)*	*(2.01)*	*(2.11)*
ANL		-0.1558***	-0.1491***	-0.1501***	-0.1465***
		(-4.54)	*(-4.35)*	*(-4.38)*	*(-4.26)*
INST		0.1693*	0.1221	0.1267	0.1100
		(1.86)	*(1.35)*	*(1.39)*	*(1.21)*
Q4		0.1226***	0.1345***	0.1328***	0.1296***
		(2.70)	*(2.97)*	*(2.93)*	*(2.86)*
LOSS		0.2477***	0.2581***	0.2565***	0.2661***
		(4.95)	*(5.13)*	*(5.09)*	*(5.28)*
N		32,418	32,418	32,418	32,418
Adj. R^2 (%)		0.26	0.21	0.20	0.25

TABLE 4, PANEL B
Tweet Opinion and Earnings Surprises at Earnings Announcements

Model: $FE = \alpha + \beta_1{*}OPI_{[-10;-2]} + \beta_2{*}SIZE + \beta_3{*}MB + \beta_4{*}ANL + \beta_5{*}INST + \beta_6{*}Q4 + \beta_7{*}LOSS + \varepsilon$

Variable	Expected Sign	Coefficient (*t-statistic*)			
		OPI1	*OPI2*	*OPI3*	*OPIFACT*
		Model I	Model II	Model III	Model IV
Intercept		-0.3146***	-0.3269***	-0.3232***	-0.3430***
		(-5.08)	*(-5.13)*	*(-5.10)*	*(-5.23)*
OPI	**+**	**0.0145****	**0.0273****	**0.0054***	**0.1070*****
		(2.07)	***(2.23)***	***(1.93)***	***(2.68)***
SIZE		0.0287***	0.0313***	0.0307***	0.0319***
		(3.32)	*(3.46)*	*(3.41)*	*(3.53)*
MB		0.0042	0.0048*	0.0046*	0.0047*
		(1.62)	*(1.83)*	*(1.77)*	*(1.82)*
ANL		0.0084	0.0098	0.0094	0.0103
		(0.40)	*(0.47)*	*(0.45)*	*(0.49)*
INST		0.2215***	0.2097***	0.2124***	0.2093***
		(4.82)	*(4.58)*	*(4.63)*	*(4.58)*
Q4		-0.0888***	-0.0872***	-0.0876***	-0.0884***
		(-4.86)	*(-4.78)*	*(-4.80)*	*(-4.84)*
LOSS		-0.2230***	-0.2193***	-0.2202***	-0.2183***
		(-7.39)	*(-7.31)*	*(-7.34)*	*(-7.30)*
N		30,181	30,181	30,181	30,181
Adj. R^2 (%)		1.31	1.32	1.31	1.33

TABLE 5
Tweet Opinion and Abnormal Stock Returns around Earnings Announcements

This table presents the results from the regressions presented below and estimated using standard errors clustered by calendar quarter and industry (using the Fama-French 48-industry classification). The sample consists of 34,040 firm-quarter observations (3,662 distinct firms), with earnings announcement dates between January 1, 2009 and December 31, 2012. *t*-statistics are in parenthesis below coefficient estimates. Coefficient estimates and *t*-statistics are bolded for the variable of interest *OPI*. $^{***}, ^{**}, ^{*}$ represent statistical significance at $p < 0.01$, $p < 0.05$, and $p < 0.10$ (two-tailed), respectively. See Appendix I for variable definitions. To mitigate the influence of outliers, all continuous variables are winsorized at the 1st and 99th percentiles.

$$\text{Model: } EXRET_{[-1;+1]} = \alpha + \beta_1 {*} OPI_{[-10;-2]} + \beta_2 {*} ANL + \beta_3 {*} INST + \beta_4 {*} Q4 + \beta_5 {*} LOSS + \varepsilon$$

Variable	Expected Sign	Coefficient (*t-statistic*)			
		OPI1	*OPI2*	*OPI3*	*OPIFACT*
		Model I	Model II	Model III	Model IV
Intercept		-0.1965*	-0.1568*	-0.1305	-0.3210***
		(-1.91)	*(-1.68)*	*(-1.41)*	*(-3.09)*
OPI	+	**0.1680*****	**0.3449*****	**0.0997*****	**1.4482*****
		(4.04)	***(7.48)***	***(6.92)***	***(9.09)***
ANL		-0.1057	-0.0473	-0.0368	-0.0317
		(-1.44)	*(-0.61)*	*(-0.45)*	*(-0.39)*
INST		0.8160***	0.6630***	0.6411**	0.6414**
		(3.29)	*(2.65)*	*(2.55)*	*(2.56)*
Q4		0.1756	0.1921	0.1850	0.1772
		(1.10)	*(1.18)*	*(1.13)*	*(1.10)*
LOSS		-0.4503**	-0.4206**	-0.4166**	-0.4120**
		(-2.28)	*(-2.18)*	*(-2.17)*	*(-2.13)*
N		33,966	33,966	33,966	33,966
Adj. R^2 (%)		0.20	0.27	0.30	0.33

TABLE 6, PANEL A

Tweet Opinion and Abnormal Stock Returns around Earnings Announcements, by Partitions of Small and Large Firms

This table (Panels A through C) presents the results from the regressions presented below and estimated using standard errors clustered by calendar quarter and industry (using the Fama-French 48-industry classification). The sample consists of 34,040 firm-quarter observations (3,662 distinct firms), with earnings announcement dates between January 1, 2009 and December 31, 2012. *t*-statistics are in parenthesis below coefficient estimates. Coefficient estimates and *t*-statistics are bolded for the variable of interest *OPI*. ***,**,* represent statistical significance at $p < 0.01$, $p < 0.05$, and $p < 0.10$ (two-tailed), respectively. See Appendix I for variable definitions. To mitigate the influence of outliers, all continuous variables are winsorized at the 1st and 99th percentiles.

$$\text{Model: } EXRET_{[-1;+1]} = \alpha + \beta_1 {*} OPI_{[-10;-2]} + \beta_2 {*} ANL + \beta_3 {*} INST + \beta_4 {*} Q4 + \beta_5 {*} LOSS + \varepsilon$$

Var.	Exp. Sign	Coefficient *(t-statistic)*											
		OPI1			*OPI2*			*OPI3*			*OPIFACT*		
		Model I			Model II			Model III			Model IV		
		SMALL	*LARGE*	*diff*	*SMALL*	*LARGE*	*diff*	*SMALL*	*LARGE*	*diff*	*SMALL*	*LARGE*	*diff*
Intercept		-0.415***	0.205	-0.619**	-0.320**	0.222	-0.542**	-0.274**	0.243	-0.517*	-0.651***	0.140	-0.791***
		(-2.58)	*(0.86)*	*(-2.15)*	*(-2.32)*	*(0.94)*	*(-1.98)*	*(-1.96)*	*(1.03)*	*(-1.89)*	*(-4.15)*	*(0.58)*	*(-2.76)*
OPI	+	**0.383*****	**0.061**	**0.321*****	**0.726*****	**0.179*****	**0.547*****	**0.199*****	**0.055*****	**0.144*****	**2.906*****	**0.764*****	**2.142*****
		(3.68)	***(1.60)***	***(2.90)***	***(5.05)***	***(5.08)***	***(3.70)***	***(4.72)***	***(4.31)***	***(3.27)***	***(5.97)***	***(5.69)***	***(4.24)***
ANL		-0.135	-0.065	-0.071	-0.114	-0.016	-0.098	-0.116	-0.005	-0.111	-0.113	-0.006	-0.107
		(-1.39)	*(-0.69)*	*(-0.52)*	*(-1.13)*	*(-0.15)*	*(-0.67)*	*(-1.14)*	*(-0.05)*	*(-0.76)*	*(-1.14)*	*(-0.05)*	*(-0.73)*
INST		1.362***	0.068	1.294***	1.243***	-0.057	1.300***	1.236***	-0.084	1.320***	1.225***	-0.072	1.297***
		(3.70)	*(0.25)*	*(2.81)*	*(3.35)*	*(-0.20)*	*(2.79)*	*(3.31)*	*(-0.30)*	*(2.84)*	*(3.33)*	*(-0.26)*	*(2.81)*
Q4		0.248	0.118	0.129	0.274	0.125	0.149	0.261	0.121	0.139	0.256	0.115	0.141
		(1.35)	*(0.88)*	*(0.57)*	*(1.51)*	*(0.90)*	*(0.65)*	*(1.43)*	*(0.86)*	*(0.61)*	*(1.40)*	*(0.83)*	*(0.62)*
LOSS		-0.450*	-0.343*	-0.107	-0.373	-0.321*	-0.052	-0.360	-0.316*	-0.045	-0.344	-0.316*	-0.028
		(-1.83)	*(-1.88)*	*(-0.35)*	*(-1.54)*	*(-1.84)*	*(-0.17)*	*(-1.50)*	*(-1.82)*	*(-0.15)*	*(-1.42)*	*(-1.80)*	*(-0.09)*
N		16,951	17,015		16,951	17,015		16,951	17,015		16,951	17,015	
Adj. R^2 (%)		0.38	0.05		0.52	0.11		0.57	0.13		0.63	0.14	

TABLE 6, PANEL B

Tweet Opinion and Abnormal Stock Returns around Earnings Announcements, by Partitions of Low and High Analyst Following

Model: $EXRET_{[-1;+1]} = \alpha + \beta_1 * OPI_{[-10;-2]} + \beta_2 * ANL + \beta_3 * INST + \beta_4 * Q4 + \beta_5 * LOSS + \varepsilon$

Var.	Exp. Sign	Coefficient *(t-statistic)*											
		OPI1			*OPI2*			*OPI3*			*OPIFACT*		
		Model I			Model II			Model III			Model IV		
		LO_ANL	*HI_ANL*	*diff*	*LO_ANL*	*HI_ANL*	*Diff*	*LO_ANL*	*HI_ANL*	*diff*	*LO_ANL*	*HI_ANL*	*diff*
Intercept		-0.361***	-0.795	0.435	-0.243**	-0.998*	0.755	-0.224*	-1.076**	0.852	-0.491***	-1.228**	0.737
		(-3.08)	*(-1.56)*	*(0.83)*	*(-2.11)*	*(-1.91)*	*(1.41)*	*(-1.89)*	*(-2.00)*	*(1.54)*	*(-4.24)*	*(-2.23)*	*(1.31)*
OPI	+	**0.187****	**0.150*****	**0.037**	**0.600*****	**0.228*****	**0.372*****	**0.142*****	**0.081*****	**0.061****	**2.128*****	**1.114*****	**1.015****
		(2.08)	***(4.23)***	***(0.38)***	***(6.88)***	***(3.69)***	***(3.48)***	***(5.62)***	***(4.52)***	***(1.98)***	***(6.11)***	***(5.33)***	***(2.50)***
ANL		0.084	0.184	-0.099	0.108	0.307	-0.200	0.103	0.367*	-0.264	0.098	0.369*	-0.271
		(0.77)	*(0.92)*	*(-0.44)*	*(1.00)*	*(1.44)*	*(-0.84)*	*(0.95)*	*(1.64)*	*(-1.06)*	*(0.90)*	*(1.64)*	*(-1.09)*
INST		0.985***	0.417	0.567	0.834***	0.303	0.530	0.847***	0.261	0.586	0.851***	0.271	0.579
		(3.03)	*(1.60)*	*(1.36)*	*(2.57)*	*(1.11)*	*(1.25)*	*(2.60)*	*(0.97)*	*(1.39)*	*(2.68)*	*(1.01)*	*(1.39)*
Q4		0.051	0.284*	-0.233	0.066	0.300**	-0.234	0.059	0.291*	-0.232	0.051	0.283*	-0.232
		(0.29)	*(1.92)*	*(-1.01)*	*(0.38)*	*(1.97)*	*(-1.01)*	*(0.33)*	*(1.91)*	*(-0.99)*	*(0.30)*	*(1.85)*	*(-1.01)*
LOSS		-0.463**	-0.446*	-0.017	-0.396*	-0.428*	0.032	-0.403*	-0.418*	0.015	-0.393*	-0.416*	0.022
		(-2.05)	*(-1.91)*	*(-0.05)*	*(-1.79)*	*(-1.91)*	*(0.10)*	*(-1.84)*	*(-1.86)*	*(0.05)*	*(-1.80)*	*(-1.84)*	*(0.07)*
N		16,945	17,021		16,945	17,021		16,945	17,021		16,945	17,021	
Adj. R^2 (%)		0.31	0.17		0.50	0.19		0.47	0.25		0.53	0.26	

TABLE 6, PANEL C

Tweet Opinion and Abnormal Stock Returns around Earnings Announcements, by Low and High Press Coverage

Model: $EXRET_{[-1;+1]} = \alpha + \beta_1 * OPI_{[-10;-2]} + \beta_2 * ANL + \beta_3 * INST + \beta_4 * Q4 + \beta_5 * LOSS + \varepsilon$

Var.	Exp. Sign	*OPI1* Model I *LO_PRESS*	*OPI1* Model I *HI_PRESS*	*OPI1* Model I *diff*	*OPI2* Model II *LO_PRESS*	*OPI2* Model II *HI_PRESS*	*OPI2* Model II *diff*	*OPI3* Model III *LO_PRESS*	*OPI3* Model III *HI_PRESS*	*OPI3* Model III *diff*	*OPIFACT* Model IV *LO_PRESS*	*OPIFACT* Model IV *HI_PRESS*	*OPIFACT* Model IV *diff*
Intercept		-0.247*	-0.023	-0.224	-0.165	0.000	-0.165	-0.145	0.015	-0.160	-0.420***	-0.141	-0.279
		(-1.67)	*(-0.13)*	*(-0.95)*	*(-1.22)*	*(0.00)*	*(-0.74)*	*(-1.07)*	*(0.09)*	*(-0.72)*	*(-2.73)*	*(-0.75)*	*(-1.15)*
OPI	**+**	**0.311*** **	**0.073**	**0.238*** **	**0.578*** **	**0.270*** **	**0.307** **	**0.136*** **	**0.087*** **	**0.049**	**2.271*** **	**1.108*** **	**1.163** **
		(5.51)	***(1.59)***	***(3.26)***	***(4.86)***	***(4.78)***	***(2.33)***	***(4.15)***	***(5.44)***	***(1.34)***	***(6.32)***	***(5.47)***	***(2.82)***
ANL		-0.139	-0.090	-0.049	-0.130	-0.011	-0.119	-0.130	0.015	-0.145	-0.120	0.006	-0.126
		(-1.37)	*(-1.49)*	*(-0.41)*	*(-1.22)*	*(-0.19)*	*(-0.98)*	*(-1.22)*	*(0.24)*	*(-1.18)*	*(-1.14)*	*(0.10)*	*(-1.04)*
INST		1.032***	0.508	0.525	0.918**	0.337	0.581	0.927***	0.295	0.632	0.907**	0.325	0.582
		(2.90)	*(1.45)*	*(1.05)*	*(2.57)*	*(1.00)*	*(1.18)*	*(2.59)*	*(0.89)*	*(1.29)*	*(2.55)*	*(0.97)*	*(1.19)*
Q4		0.330	0.035	0.294	0.352*	0.044	0.308	0.343*	0.037	0.306	0.333*	0.030	0.303
		(1.79)	*(0.23)*	*(1.23)*	*(1.90)*	*(0.28)*	*(1.27)*	*(1.83)*	*(0.23)*	*(1.25)*	*(1.83)*	*(0.19)*	*(1.26)*
LOSS		-0.533***	-0.361*	-0.171	-0.484***	-0.334	-0.150	-0.489***	-0.327	-0.162	-0.473***	-0.328	-0.145
		(-3.73)	*(-1.68)*	*(-0.66)*	*(-3.40)*	*(-1.57)*	*(-0.59)*	*(-3.45)*	*(-1.52)*	*(-0.63)*	*(-3.36)*	*(-1.52)*	*(-0.56)*
N		16,925	17,041		16,925	17,041		16,925	17,041		16,925	17,041	
Adj. R^2 (%)		0.38	0.08		0.43	0.17		0.43	0.22		0.53	0.21	

Coefficient *(t-statistic)*