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

Eli Bartov
Leonard N. Stern School of Business
New York University
ebartov@stern.nyu.edu

Lucile Faurel
W.P. Carey School of Business
Arizona State University
lucile.faurel@asu.edu

Partha Mohanram
Rotman School of Management
University of Toronto
partha.mohanram@rotman.utoronto.ca

The Accounting Review July 2018 (forthcoming).

ABSTRACT: Prior research has examined how companies exploit Twitter in communicating with investors, and whether Twitter activity predicts the stock market as a whole. We test whether opinions of individuals tweeted just prior to a firm's earnings announcement predict its earnings and announcement returns. Using a broad sample from 2009 to 2012, we find that the aggregate opinion from individual tweets successfully predicts a firm's forthcoming quarterly earnings and announcement returns. These results hold for tweets that convey original information, as well as tweets that disseminate existing information, and are stronger for tweets providing information directly related to firm fundamentals and stock trading. Importantly, our results hold even after controlling for concurrent information or opinion from traditional media sources, and are stronger for firms in weaker information environments. Our findings highlight the importance of considering the aggregate opinion from individual tweets when assessing a stock's future prospects and value.

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

This paper benefited from conversations with Professor Rafi Eldor from the Interdisciplinary Center (IDC) in Israel, and comments and suggestions from Roger Martin, Capt. N.S. Mohanram, Mihnea Moldoveanu, and workshop participants at: Columbia University, University of California Irvine, University of Miami, Wilfrid Laurier University, the 2016 Asian Bureau of Finance and Economic Research (ABFER) 4th Annual Conference, the 2016 Canadian Academic Accounting Association (CAAA) Annual Conference. Partha Mohanram acknowledges financial support from the Social Sciences and Humanities Research Council (SSHRC) of Canada.

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

I. INTRODUCTION

Investors have long relied on information intermediaries (e.g., financial analysts, financial advisors, the business press, credit rating agencies, short sellers, auditors) to acquire timely and value-relevant information regarding the prospects of stocks. However, the past decade has witnessed an explosion in new sources of information that are easily accessible to capital market participants. With the rise of the Internet, individual investors are increasingly relying on each other as peer-to-peer sources of information (e.g., Yahoo! Finance, Silicon Investor, and Raging Bull). By far, however, the biggest revolution in the dissemination of information on the Internet has been the advent of social media platforms such as Twitter, which allow users to post instantaneously their views about stocks to a wide audience.[1]

While Twitter undoubtedly is an exciting and emerging new source of information to the capital market, *ex-ante* it is unclear whether information from Twitter will be useful to investors. On one hand, Twitter allows users to tap into the Wisdom of Crowds, where the aggregation of information provided by many (non-expert) individuals often predicts outcomes more precisely than experts. Further, Twitter users, who come from diverse backgrounds, are less likely to herd, a phenomenon that plagues traditional information intermediaries (e.g., financial analysts), as well as social media platforms (e.g., blogs, investing portals) where a central piece of information is

[1] The importance of Twitter as a valuable source of information has not gone unnoticed by practitioners. In 2015, Tashtego, a hedge-fund firm based in Boston, set up a Social Equities Fund with investment decisions based on sentiment from social media (http://fortune.com/2015/04/02/hedge-fund-twitter/). Further, DataMinr, a start-up firm that parses Twitter feeds to generate actionable real-time signals, announced that it had raised over $130 million in financing (http://www.wsj.com/articles/tweet-analysis-firm-dataminr-raises-funding-1426564862). In addition, on April 26, 2016, Infinigon Group announced the launch of ECHO™, its Twitter-based financial information platform that converts social media data streams into early, pre-mainstream, actionable news and analytics important to the trading community (http://www.prweb.com/releases/2016/04/prweb13376503.htm).

posted and users comment on it. Finally, Twitter's short format (up to 140 characters) and ease of information search (e.g., the use of cashtags) make it an ideal medium to share opinions and information in a timely fashion, in contrast to the longer format and potentially reduced timeliness of research reports or articles.[2]

On the other hand, the information from tweets may be uninformative or even intentionally misleading, because Twitter is an unregulated platform with potentially anonymous users. For example, in two days in January 2013, a series of damning, but false tweets on two stocks—Audience Inc. (ticker symbol: ADNC) and Sarepta Therapeutics, Inc. (ticker symbol: SRPT)—sent their prices plunging by 28 percent and 16 percent, respectively.[3]

The academic literature has begun studying the role Twitter plays in the capital market only recently, perhaps because Twitter was created in March 2006 and launched in July 2006. One strand of this literature examines how companies exploit this new channel to communicate with investors, another investigates whether information from Twitter predicts the overall stock market, and a third analyzes the relation between Twitter activity and investor response to earnings news.

However, the intriguing question of whether firm specific information from Twitter is useful in predicting a firm's earnings and stock returns has not been addressed. In this paper, we fill this gap in the literature by examining whether information from individual tweets about a firm

---

[2] Tweets are limited to 140 characters due to the 160-character limit for text messaging, allowing 20 characters for the user's username. Cashtags are stock ticker symbols that are prefixed with a dollar sign. For example, to tweet about Starbucks' stock, a user would use $SBUX.

[3] The two tweets are: (i) "*AUDIENCE the noise suppression company being investigated by DOJ on rumoured fraud charges Full reort* [sic] *to follow later*", and (ii) *"$SRPT FDA steps in as its 48 weeks results on Etelplisen [sic] results are tainted and have been doctored they believe Trial papers seized by FDA*." Interestingly, the perpetrator—who used two accounts using aliases similar to well-known short-selling firms Muddy Waters and Citron Research with misspellings—managed to net only $97, as investors quickly figured out the deceit, and the share prices almost instantly recovered. Other instances consist of Twitter users misleading entire markets with false information. In 2010, the Australian airline company Qantas saw its stock price decline by more than 10 percent 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 percent decline in the value of the *S&P 500* Index, representing $130 billion in stock value.

can help investors predict the firm's earnings and announcement returns. Specifically, we explore the following three research questions: (1) Does the aggregate opinion from individual tweets pertaining to a firm predict its quarterly earnings? (2) Does the aggregate opinion from individual tweets predict the stock price reaction to the firm's earnings realizations? (3) Does the information environment quality of a company explain the cross-sectional variation in the predictive ability of the aggregate opinion from individual tweets (if it exists)?

To study our three research questions, we develop a test variable, *OPI* (for opinion), which captures the aggregate opinion on a stock gleaned from individual tweets. We estimate *OPI* by first quantifying the content of each tweet using textual analysis, and then aggregating the textual-analysis result across all tweets by firm-quarter. Our *OPI* variable is a signed measure of the aggregate opinion from Twitter, with higher values representing more positive (or less negative) opinion, and lower values representing more negative (or less positive) opinion. To mitigate the well-known concern that textual analysis is inherently imprecise, we employ two alternative textual-analysis approaches to estimate *OPI*. The variable from the first approach, *OPI_BAYES*, is based on a naïve Bayes algorithm that classifies individual tweets as positive, negative, or neutral. The variable from the second approach, *OPI_VOCAB*, is derived from commonly-used dictionaries that identify the number of negative words in each individual tweet.

In addition to testing our three research questions using *OPI* as our test variable, we attempt to distinguish between different types of tweets using two classification schemes. The first classification separates tweets conveying original information from those disseminating existing information. The second classification splits tweets conveying information related to earnings, firm fundamentals, and/or stock trading from those communicating other information.

We employ a broad sample of 869,733 tweets (covering 33,186 firm-quarters from 3,604 distinct *Russell 3000* firms) that span the four-year period, January 1, 2009 to December 31, 2012. Our sample only covers tweets providing information related to a stock, written by individuals in the nine-trading-day period leading up to the firm's quarterly earnings announcement (days -10 to -2, where day 0 is the earnings announcement day). Our analysis focuses on earnings announcements because they are recurring, high impact corporate events, scrutinized closely by capital market participants.

We document three sets of findings. First, we demonstrate the ability of the aggregate opinion from individual tweets, *OPI*, to predict the company's quarterly earnings. Both *OPI_BAYES* and *OPI_VOCAB* show a positive association with the future realized earnings surprise, after controlling for determinants of earnings documented by prior research, as well as the opinion from traditional media channels. Second, we document a positive association between the immediate stock price reaction to the quarterly earnings announcement and both *OPI_BAYES* and *OPI_VOCAB*. When classifying tweets into original and dissemination, we find little difference in *OPI*'s ability to predict earnings and announcement returns across these two categories. Thus, Twitter serves a dual role in the capital market: conveying original information about stocks' prospects and values, as well as disseminating existing information. Furthermore, when considering tweets that convey information directly related to earnings, firm fundamentals, and/or stock trading, and those containing other information, we find that the former are more important in predicting earnings, yet both types of tweets exhibit a similar association with announcement returns. Third, the predicted stock price reaction to earnings announcements by the aggregate Twitter opinion is stronger for firms in weak information environments. This last finding suggests that weak information environment settings magnify the importance of Twitter as a source of information.

Overall, our findings highlight the importance for capital market participants to consider information on stocks from Twitter when assessing stocks' future prospects and value. These findings make two important contributions. First, they have important implications for the role Twitter plays in the investing community. While stock investing may be viewed as a non-cooperative, zero-sum game, our results suggest that individuals use Twitter as an important channel to share information regarding stocks for their mutual benefit.

Second, our results are important to regulators. Skeptics may argue that self-serving 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 decisions. 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 remainder of the paper is organized as follows. Section II presents a review of the literature. Section III delineates the Wisdom of Crowds concept. Section IV develops our research questions, and outlines the research design. Section V describes the data, Section VI presents the primary empirical results, and Section VII outlines the results from supplementary tests. The final section, Section VIII, summarizes our main findings and conclusions.

II. LITERATURE REVIEW

In recent years, the academic literature has begun studying the role Twitter plays in the capital market. One strand of this literature investigates how companies exploit this new channel to communicate with investors. Blankespoor, Miller, and White (2014) show that firms can reduce information asymmetry among investors by more broadly disseminating their news using Twitter to send market participants links to press releases and other traditional disclosures. Jung, Naughton, Tahoun, and Wang (2016) find that roughly half of *S&P 1500* firms have created either a corporate Twitter account or a Facebook page, with a growing preference for Twitter.[4] Lee, Hutton, and Shu (2015) 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 information from Twitter predicts the overall stock market. Bollen, Mao, and Zheng (2011) show that aggregate mood inferred from textual analysis of daily Twitter feeds can help predict changes in the Dow Jones Index. Similarly, Mao, Wei, Wang, and Liu (2012) find that the daily number of tweets that mention *S&P 500* stocks is significantly associated with the levels, changes, and absolute changes in the *S&P 500* Index. A third strand of this literature analyzes how Twitter activity influences investor response to earnings. Curtis, Richardson, and Schmardebeck (2016), who focus on the overall social media (Twitter and StockTwits) activity over 30-day rolling windows, find that high levels of activity are associated with greater sensitivity of earnings announcement returns to earnings surprises, while low levels of social media activity are associated with significant post-earnings-announcement drift.

In addition to the literature on Twitter, a broad stream of research has examined investors' use of Internet search engines, financial websites, forums, and other social media platforms. This research has provided mixed evidence on whether this information helps predict future earnings and stock returns. Using Google search volume as a proxy for investors' demand for financial information, Da, Engelberg, and Gao (2011) find that increases in Google searches predict higher

[4] In June of 2015, the SEC's staff, in a "Compliance and Disclosure Interpretations," said a startup firm 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.

stock prices in the near-term followed by a price reversal within a year, while Drake, Roulstone, and Thornock (2012) show that the returns-earnings relation is smaller when Google search volume prior to earnings announcements is high. Examining Internet bulletin boards, Hirschey, Richardson, and Scholz (2000) find that investment reports in Motley Fool predict stock returns, whereas Tumarkin and Whitelaw (2001) find no link between message board activity on Raging Bull and stock returns. Antweiler and Frank (2004) and Das and Chen (2007) both find that the volume of messages on message boards, such as Yahoo! or Raging Bull, is associated with stock return volatility, but not stock returns. More recently, Jame, Johnston, Markov, and Wolfe (2016) show that crowdsourced earnings forecasts on the Estimize platform provide incrementally value relevant information to capital market to predict earnings and calibrate the market's expectation of earnings. Finally, Chen, De, Hu, and Hwang (2014) demonstrate that information in user-generated research reports and commentaries on the SeekingAlpha portal helps predict earnings and long-window stock returns following the report posting date. However, unlike investing portals such as SeekingAlpha that publish paid, full-length reports from registered users after verifying their credentials and vetting the quality of the submissions, there is little control or monitoring on an open platform such as Twitter.[5]

What left unexplored by these literatures, however, is the question of whether firm specific information from individual tweets is useful in the prediction of the firm's earnings and stock returns, the very question we examine in our paper.

[5] Twitter users may file reports if they believe that a posted tweet is in violation of Twitter's Rules or Terms of Service. However, these violations never relate to the content of the tweet, and generally relate to issues such as impersonation, trademark or copyright infringement, violence or threat, etc. See details at https://support.twitter.com/articles/18311.

III. WISDOM OF CROWDS

The Wisdom of Crowds concept 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 member of the group, or even experts. Surowiecki (2004) presents numerous case studies and anecdotes to illustrate the Wisdom of Crowds. 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.[6] 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 estimates made by cattle experts. Similarly, trial by jury can be understood as a manifestation of the Wisdom of Crowds, especially when compared to trial by a judge, the single expert.

Berg, Forsythe, Nelson, and Rietz (2008) analyze the ability of the Iowa Electronic markets to predict election results and find that the markets' prediction show no bias and remarkable ability to predict high profile elections, outperforming polls conducted by experts. Recent papers that build on the Wisdom of Crowds notion show that user-generated research reports and commentaries posted on the SeekingAlpha portal help predict stock returns in several long-term intervals following the report posting date (Chen et al. 2014), and that the content of tweets can be used to predict future returns around Federal Open Market Committee (FOMC) meetings (Azar and Lo 2016).

In related work, Hong and Page (2004) show analytically that a diverse group of intelligent decision makers reaches reliably better decisions than a less diverse group of individuals with superior skills, and conclude that under certain conditions, "diversity trumps ability," (p. 16386).

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

Building on this, Moldoveanu and Martin (2009, pp. 163–164) in their book, "*Diaminds: Decoding the Mental Habits of Successful Thinkers*," conclude: "A collection of heterogeneous problem solvers will always beat out a single expert problem solver." This is relevant to the research questions of this paper, because anecdotal evidence suggests that Twitter has the most diverse set of users among social media platforms.[7] In contrast, traditional information intermediaries such as financial analysts tend to "herd" to the consensus viewpoint (Jegadeesh and Kim 2010) and produce inefficient earnings forecasts (see, e.g., Abarbanell 1991; Abarbanell and Bernard 1992; Stevens and Williams 2004), perhaps because they belong to a rather small and homogenous group (see, e.g., Welch 2000; Hong, Kubik, and Solomon 2000).

To summarize, if the Wisdom of Crowds and the value of diversity and independence apply to the information on the Twitter platform, this information may be helpful in the prediction of a firm's earnings and announcement returns.

IV. RESEARCH QUESTIONS AND DESIGN

Can Aggregate Opinion Predict Earnings Surprises?

Our first research question asks, can the aggregate opinion from individual tweets regarding a company, expressed by individuals just prior to its earnings announcement, predict the company's earnings? An implication of the Wisdom of Crowds and the value of diversity and independence concepts is that the aggregation of opinions derived from individual tweets may help in predicting earnings. This would be the case when individual tweets reflect opinions of a *large* and *diverse* group of people making *independent* and *timely* assessments of a company's future earnings. Specifically, positive aggregate opinion may suggest company performance that exceeds prior expectations, while negative aggregate opinion may suggest company performance that

[7] http://mashable.com/2014/01/23/racial-breakdown-social-networks/#0ecOTuMGhmqV

disappoints prior expectations. To test our first research question, we thus estimate the following model:

$$ESURP = \alpha + \beta_1 * OPI_{[-10;-2]} + \beta_2 * PRIOR\_ESURP + \beta_3 * EXRET_{[-10;-2]} + \beta_4 * RP\_OPI \\ + \beta_5 * SIZE + \beta_6 * MB + \beta_7 * ANL + \beta_8 * INST + \beta_9 * Q4 + \beta_{10} * LOSS + \varepsilon \qquad (1)$$

In Equation (1), which is a forecasting model, the dependent variable, *ESURP*, is the earnings surprise, measured using either standardized unexpected earnings (*SUE*) or analyst earnings forecast error (*FE*), as is standard in the literature. All variables are defined in detail in Appendix A. *SUE* is measured using quarterly diluted earnings per share, excluding extraordinary items, and applying a seasonal random walk with a drift model literature (e.g., Bernard and Thomas 1990; Ball and Bartov 1996). *FE* is the I/B/E/S reported quarterly EPS less the latest I/B/E/S consensus analyst quarterly EPS forecast just prior to the earnings announcement, scaled by the stock price as of the forecast date, multiplied by 100 (see, e.g., Ng, Rusticus, and Verdi 2008). The test variable, $OPI_{[-10;-2]}$, is the aggregate opinion about a firm extracted from individual tweets written in the period, -10 to -2, where day 0 is the firm's quarterly earnings announcement date. *OPI* is a signed measure of the aggregate opinion from Twitter, with higher values representing more positive opinion and lower values representing more negative opinion. In Equation (1), the hypothesis that the aggregate opinion from individual tweets predicts the upcoming earnings surprise implies $\beta_1 > 0$.

The primary challenge underlying our research design is the estimation of *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* using two alternative, and considerably different, textual-analysis methodologies. The first methodology considers each individual tweet as a whole and classifies it as negative, positive, or neutral. The second methodology focuses on the words included in each individual tweet and detects specific negative words in the tweet.

Each methodology presents strengths and weaknesses. The first methodology considers the message as a whole and thus may seem more appropriate for analyzing the tweet's content. Moreover, this approach employs an enhanced algorithm, which handles negation and considers bigrams and trigrams (i.e., sets of two or three consecutive words), among other features. However, this method would be expected to have potentially large measurement error in case the algorithm does not correctly detect the overall meaning of the message. Further, the accuracy of this classifier was developed and tested using movie reviews. Even if movie review data is commonly used to benchmark sentiment classification (Narayanan, Arora, and Bhatia 2013), it is unclear whether the methodology would be directly applicable to tweets about stocks and companies. Conversely, the second methodology focuses on specific words included in each tweet, and consequently may be more precise. The word lists employed were developed to analyze various types of text, such as financial disclosures (e.g., the Loughran and McDonald 2011 word list), general text (e.g., the Harvard IV-4 word list), or customer reviews (e.g., the Hu and Liu 2004 word list). Still, none was created specifically to study tweets. Furthermore, this approach does not involve machine learning, and the number of negative words in a tweet may not reflect the overall opinion of the message. Thus, this approach may lack accuracy. Given these tradeoffs, we employ both methodologies to capture the aggregate opinion from individual tweets.

The first measure, *OPI_BAYES*, is based on the enhanced naïve Bayes algorithm developed by Narayanan et al. (2013) that classifies each tweet as either positive, negative, or neutral, and provides a probability level (between 50 and 100 percent) for reliability. To compute *OPI_BAYES*, we first weight each tweet by its probability. Next, along the lines of Barberis, Shleifer, and

Vishny (1998), we weight each tweet by a metric that captures the strength and salience of the source, using the number of followers of the Twitter user as a measure of how important the user's opinion is in providing relevant information to predict the upcoming earnings news and earnings announcement returns.[8] Specifically, we weight each tweet by {1 + [Log(1 + Number of Followers)]}. Finally, we derive *OPI_BAYES* by taking the difference between the weighted number of positive and negative tweets, and scaling the difference by one plus the sum of the probability levels.[9]

The second measure, *OPI_VOCAB*, is the single factor constructed from a factor analysis using three vocabulary-based measures, each related to a word list (or dictionary) commonly used in the literature: the Loughran and McDonald (2011) word list, the Harvard IV-4 word list, and the Hu and Liu (2004) word list. These three measures are based on the identification in each tweet of words from each dictionary. These word lists identify only negative words, as prior research indicates that only negative word classifications can be effective in measuring tone (e.g., Tetlock 2007; Engelberg 2008; Loughran and McDonald 2011). Using each word list, we first weight the number of words classified as negative in each tweet by {1 + [Log(1 + Number of Followers)]}. Then, we compute an *OPI* measure as minus one multiplied by the sum of the weighted number of negative words in all tweets during the nine-day window [-10;-2], scaled by one plus the number of words classified as either positive or negative. We then use factor analysis to combine the three *OPI* measures. As these three underlying *OPI* measures are strongly correlated with each other,

[8] As a sensitivity analysis, we replicate our tests using the number of past posts on Twitter to capture the strength and salience of the source. The (untabulated) results are qualitatively similar to the tabulated results. Likewise, the inferences from our results remain unchanged if we do not include weights.

[9] Scaling by the sum of the probability levels for *OPI_BAYES* is similar to scaling by the total number of positive and negative words for *OPI_VOCAB*; both approaches control for the extent of information in tweets in the period [-10;-2] as well as Twitter activity across firms and over time. As discussed in Section VII, we test three alternative deflators, and find our results to be robust to this research design choice.

the factor analysis yields a single factor, which we label as *OPI_VOCAB*.[10]

To estimate Equation (1), we first consider all tweets when computing *OPI*. We then refine our analysis by classifying tweets using two alternative schemes and computing *OPI* for each classification. In the first scheme, we distinguish between tweets that contain original information ("*ORIG*" for original) and those that relay or disseminate existing information ("*DISSEM*" for dissemination). This classification allows us to compare and contrast the dual role of Twitter as a source of new information and a means of disseminating existing information. In the second classification scheme, we distinguish between tweets that explicitly convey information about a firm's earnings, fundamentals, and/or stock price ("*FUNDA*" for fundamental) and tweets that contain other information ("*NONFUNDA*" for non-fundamental). This refinement allows us to cast light on the nature of information that tweets convey. Appendix B outlines in detail the procedures we use to classify tweets into *OPI_ORIG* and *OPI_DISSEM* as well as into *OPI_FUNDA* and *OPI_NONFUNDA*. It is important to note that our classification heuristics might be subject to a degree of error, especially the decomposition between original and dissemination tweets. Specifically, some of the tweets we classify as original might be based on other sources of information, but without proper attribution by the Twitter user.

Finally, the control variables comprise: *PRIOR_ESURP*, the lagged earnings surprise from the previous quarter, included to control for the well-documented positive autocorrelation in earnings surprises; $EXRET_{[-10;-2]}$, Carhart's (1997) four factor buy-and-hold abnormal stock returns for the firm over the window [-10;-2], multiplied by 100, included to control for information, other than through Twitter, that may have reached the capital market prior to the earnings release; *RP_OPI*, a measure of the aggregate opinion from traditional news over the period -10 to -2,

[10] Appendix C provides examples of tweets and illustrates how the various textual-analysis methodologies quantify their content.

developed from the RavenPack database to control for information and opinion from traditional news media; *SIZE*, firm size; *MB*, market-to-book ratio; *ANL*, number of analysts in the consensus I/B/E/S/ quarterly earnings forecast; *INST*, institutional investor holding; *Q4*, indicator variable for the fourth fiscal quarter; and *LOSS*, an indicator variable for past quarterly loss. These last six variables control for effects shown by prior research to explain the cross-sectional variation in earnings surprises.

Can Aggregate Opinion Predict Announcement Returns?

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

$$EXRET_{[-1;+1]} = \alpha + \beta_1 * OPI_{[-10;-2]} + \beta_2 * EXRET_{[-10;-2]} + \beta_3 * RP\_OPI + \beta_4 * ANL + \beta_5 * INST + \beta_6 * Q4 + \beta_7 * LOSS + \varepsilon \quad (2)$$

In Equation (2), the dependent variable, $EXRET_{[-1;+1]}$, is Carhart's (1997) buy-and-hold abnormal stock returns for the firm over the three-day window, [-1;+1], multiplied by 100. $OPI_{[-10;-2]}$, the test variable in Equation (2), captures the aggregate opinion at the firm-quarter level extracted from individual tweets written in days -10 to -2. As described above, it is measured using *OPI_BAYES* and *OPI_VOCAB*, and disaggregated into *OPI_ORIG* and *OPI_DISSEM*, as well as *OPI_FUNDA* and *OPI_NONFUNDA*.

The other six explanatory variables in Equation (2) are defined above with Equation (1) and in Appendix A.[11] The first variable, $EXRET_{[-10;-2]}$, controls for momentum in stock returns, and is included to ensure that the effects we attribute to our variable of interest (*OPI*) are not driven by momentum of pre-announcement returns. The second variable, *RP_OPI*, is included to ensure

[11] Unlike Equation (1), we do not include *SIZE* and *MB* in Equation (2) as the dependent variable *EXRET* controls for size and book-to-market. As expected, results are unaltered if we include these two variables in Equation (2).

that the Twitter-based *OPI* variables are not merely capturing information and opinion from traditional media sources. The other four variables are used to control for effects shown by prior research to explain the cross-sectional variation in stock returns around earnings announcements.

In Equation (2), the prediction that the aggregate opinion from individual tweets predicts earnings announcement returns implies $\beta_1 > 0$. This would 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, but does not extract earnings information from other, less prominent sources such as tweets in a timely fashion (i.e., as they are released). It is arguable, however, that the marginal investor who sets stock prices 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.

Role of the Information Environment

Our final research question examines the impact of the information environment on the relation between the aggregate opinion from individual tweets and stock returns around earnings announcements. For firms in strong information environments, it is plausible that the information from individual tweets is already known to the capital market through channels such 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 between the firm and market participants is substantial, the aggregate Twitter opinion may provide important incremental information.

Indeed, the information environment is a multifaceted and multidimensional concept that is likely associated with the following three factors: analyst following, institutional investment, and traditional media coverage. Thus, to isolate instances of weak information environment surrounding a firm, we define an indicator variable labeled *POORINFO*, which equals one if analyst following, institutional investment, and traditional media coverage are all below sample medians in the same calendar quarter, and zero otherwise. We then rerun Equation (2) after adding an interaction of *POORINFO* with our *OPI* variables as well as with the *RP_OPI* control variable, to allow for a differential effect of the aggregate opinion from Twitter and traditional media for firms in strong and weak information environments. More formally, we use the following specification:

$$\begin{aligned} EXRET_{[-1;+1]} = {} & \alpha_1 + \alpha_2 * POORINFO + \beta_1 * OPI_{[-10;-2]} + \beta_2 * OPI_{[-10;-2]} \times POORINFO \\ & + \beta_3 * EXRET_{[-10;-2]} + \beta_4 * RP\_OPI + \beta_5 * RP\_OPI \times POORINFO \\ & + \beta_6 * ANL + \beta_7 * INST + \beta_8 * Q4 + \beta_9 * LOSS + \varepsilon \end{aligned} \tag{3}$$

In Equation (3), the coefficient β_1 represents the contribution of *OPI* in predicting announcement returns for firms in strong information environments, and the coefficient β_2 represents the incremental contribution of *OPI* in predicting stocks returns for firms in weak information environments. Hence, our prediction that the effect of the aggregate Twitter opinion on announcement returns is stronger for firms in weak information environments implies $\beta_2 > 0$. All other variables are as defined above, in Equations (1) and (2).

V. SAMPLE SELECTION AND DATA

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 tweets with cashtags, i.e., stock symbols preceded by the dollar sign (e.g., $AAPL for Apple Inc.; $PEP for PepsiCo Inc.).[12] We limit our sample to tweets with cashtags, in an effort to increase confidence that the tweets relate to the firm

[12] To facilitate further the communication of financial information, Twitter started making cashtags clickable in July of 2012. A click on a cashtag takes users to a search for tweets with this cashtag. The introduction of this feature, however, had little impact on the prevalence of cashtags, as the ratio of tweets with cashtags to all tweets remained fairly constant over the three-year period, April 2011 to April 2013 (see, Hentschel and Alonso 2014, Table 1).

financial performance and value, thereby increasing the relevance 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) with cashtags from *Russell 3000* firms between March 21, 2006 and December 31, 2012. Following Da et al. (2011), our sample contains all stocks ever included in the *Russell 3000* Index during our sample period. Dropping tweets containing multiple stock symbols, to know what stock each tweet refers to, reduces the sample to 8,713,182 tweets (61,357 firm-quarters from 4,668 unique firms). Next, we require that the firms mentioned in the tweets are 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 prior to December 17, 2008 (i.e., ten trading days before January 1, 2009), due to limited Twitter activity and limited use of cashtags 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).

Given our interest in the predictive ability of tweets just prior to the earnings release, we focus only on tweets written in the nine-trading-day period [-10;-2] leading to the earnings announcement (day 0), released over the period January 1, 2009 to December 31, 2012. This results in a sample of 998,495 tweets (34,040 firm-quarters from 3,662 unique firms). Finally, we manually clean the list of ticker symbols and cashtags in our sample to eliminate: i) tweets in which the ticker symbol mentioned has a generic meaning and does not refer to a company's stock (e.g., $CASH, $GDP, $M, etc.), and ii) tweets in which the "$" symbol is used, not as a cashtag, but rather to refer to a generic word along with the joined letters (e.g. $ALE for sale; $LOW for slow; $WAG for swag). Our final sample consists of 869,733 tweets, covering 33,186 firm-quarters from 3,604 distinct *Russell 3000* firms, written by individuals in the nine-trading-day period leading up to firms' quarterly earnings announcements between January 1, 2009 and December 31, 2012.[13]

Descriptive Statistics on Twitter Activity

Table 2 presents the descriptive statistics on Twitter activity for our sample. Panel A presents the frequency distributions by calendar quarter.[14] There has been a dramatic increase in Twitter activity over our sample period. Within our sample, the number of tweets per calendar quarter increases dramatically from 3,297 tweets in the first quarter of 2009 to 124,067 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 538 in the first quarter of 2009 to 3,068 in the fourth quarter of 2012.

Panel B of Table 2 presents descriptive statistics related to tweets and Twitter users. Given the 140-character limit, the mean and median lengths of tweets in our sample are only 13 words. Also, Tweets have a mean (median) of 4,127 (78) followers and 9,351 (3,543) prior tweets. Finally, a given firm-quarter has a mean (median) of 14 (5) distinct users tweeting about the same firm.

Panel C of Table 2 presents comparisons of the sample distributions of tweets and firm-quarters by the Fama-French 48 industry groupings with that of the Compustat universe. Generally, our sample tweets and firms span all 48 industries and their distribution across industries is fairly similar to that of Compustat. Thus, there is little evidence of industry clustering within our sample. Still, it appears that the Computers industry (Group 35 that includes most of

[13] The sample sizes for the tests reported in Tables 4-8 are (slightly) smaller and vary from 33,114 to 28,784 firm-quarters due to additional data requirements.

[14] 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 27, 2009 are included in the calendar quarter "2009, Jan-Mar."

the high technology firms and firms in "new economy" sectors) draws special attention of Twitter users. While this group represents only 3.42 percent of our firm-quarters and 2.84 percent of the Compustat universe, the number of tweets related to stocks in this group (140,657) represents 16.17 percent of all tweets in our sample (869,733). To address problems arising from potential industry clustering within the sample, we use bootstrapped cluster-robust standard error estimators when estimating Equations (1), (2), and (3).[15]

Descriptive Statistics for the Analysis Variables

Panel A of Table 3 presents the descriptive statistics for the analysis variables. Our first opinion variable, *OPI_BAYES*, the only measure considering both positive and negative information from tweets, appears to show negative skewness with a negative mean, -0.099, but a zero median. This might suggest a "bad-news" bias in tweets, following from investors being more likely to share their pessimism on social media than optimism. Turning to *OPI_VOCAB*, which considers only negative words in tweets and is derived from factor analysis, we note that the mean is zero by construction and the winsorized mean is close to zero (0.005).

Our two earnings surprise variables, standardized unexpected earnings (*SUE*) and analyst forecast error (*FE*), appear to differ slightly; the mean and median *SUE* are both negative, -0.151 and -0.010, respectively, while *FE* has a positive mean and median, 0.003 and 0.067 percent, respectively. Our measure of abnormal returns around earnings announcements, $EXRET_{[-1;+1]}$, has a slightly positive mean, 0.014 percent, and a slightly negative median, -0.017 percent.

[15] Along the lines of prior research (e.g., Petersen 2009), we cluster standard errors by firm when *SUE* and *FE* are the dependent variables, i.e., when estimating Equation (1), because the errors may be correlated over time at the firm level. We cluster standard errors by calendar quarter and industry when the dependent variable is $EXRET_{[-1;+1]}$, i.e., when estimating Equations (2) and (3), because the errors may be correlated in the same calendar period across firms. To address concerns related to estimation errors due to few clusters (especially with respect to calendar quarters), we use bootstrapped clustered standard errors (see, e.g., Petersen 2009; Cameron, Gelbach, and Miller 2011; Cameron and Miller 2015).

RP_OPI, the measure of aggregate opinion from traditional news media, has a positive mean, 0.105, suggesting *prima facie* that the information from Twitter with its negative bias may provide an interesting counterpoint to information from traditional media. The firm size statistics (*ASSETS* and *MVE*) suggest that the sample spans firms of all sizes. The mean market-to-book ratio (*MB*) is 3.082, suggesting that the sample includes many "growth" and intangible-intensive firms. The sample also consists of firms in relatively strong information environments, as evidenced by the mean *ANL* of 1.895, which corresponds to an average of over five analysts, and the first quartile of *ANL*, 1.386, which corresponds to approximately three analysts. The mean firm has 63.3 percent of its shares held by institutional investors. Finally, slightly less than a quarter of our sample (22.7 percent) corresponds to earnings announcements of fourth quarter results (*Q4*), while slightly more than a quarter of our sample (26.7 percent) reports a quarterly loss in the previous quarter.

Correlation Coefficients

Panel B of Table 3 presents pairwise correlation coefficients among our analysis variables. Figures above and below the diagonal represent, respectively, Spearman and Pearson correlations. The variables include the two measures of aggregate opinion (*OPI_BAYES* and *OPI_VOCAB)*, earnings surprise (*SUE*), forecast error (*FE*), abnormal stock returns around earnings announcements (*EXRET*), and the control variables.

The two opinion variables, *OPI_BAYES* and *OPI_VOCAB*, show a modest positive pairwise correlation (0.14 and 0.12, using Spearman and Pearson, respectively), suggesting that they may be capturing different aspects of aggregate investor opinion. In addition, *OPI_BAYES* and *OPI_VOCAB* have positive correlations with each of our three dependent variables, *SUE*, *FE*, and $EXRET_{[-1;+1]}$. This may be viewed as *prima facie* evidence of the predictive ability of the aggregate opinion from individual tweets regarding a firm's future earnings and returns.

As one would expect, both *SUE* and *FE* show positive pairwise correlations. The opinion variables are correlated negatively with size, analyst following, and institutional ownership. Finally, the relatively small pairwise correlation coefficients among our control variables indicate there is little evidence of a multi-collinearity problem in our data (one notable exception is the well-documented high correlation between size and analyst following).

VI. PRIMARY FINDINGS

Aggregate Opinion from Individual Tweets and Earnings Surprises

Our first research question pertains to the ability of social media to predict quarterly earnings. Can opinion aggregated from individual tweets regarding a firm help predict the firm's quarterly earnings? To answer this question, we perform regression tests, estimating Equation (1) using bootstrapped standard errors clustered by firm, as described above.

Table 4, Panel A, presents the results for the overall aggregate opinion variables. In Models I and II, the dependent variable is *SUE*, with Model I (Model II) reporting the results using *OPI_BAYES* (*OPI_VOCAB*). As the results show, *OPI_BAYES* is significantly positive, with a coefficient of 0.0275 (*t*-statistic = 2.84), and similarly *OPI_VOCAB* is significantly positive, with a coefficient of 0.3138 (*t*-statistic = 13.98).

Among the control variables, it is noteworthy that the prior earnings surprise, *PRIOR_ESURP*, the prior abnormal stock returns, $EXRET_{[-10;-2]}$, and the opinion from traditional media, *RP_OPI*, all have significantly positive coefficients in both specifications. The estimate on *PRIOR_ESURP* is expected to be significantly positive in light of a similar finding in prior research indicating a positive serial correlation in quarterly earnings surprises (e.g., Bernard and Thomas 1990; Ball and Bartov 1996). The finding that the coefficient on $EXRET_{[-10;-2]}$—which is included to control for information other than through Twitter that may have reached the capital market prior to the earnings release—is significant is not surprising because $EXRET_{[-10;-2]}$ reflects current earnings information not yet included in *SUE*. Finally, the significantly positive coefficient on *RP_OPI* indicates that the correlation between the aggregate Twitter opinion variables and future earnings surprise is incremental to the effect of information and opinion from traditional media sources. Taken together, the results provide consistent support that the aggregate opinion from individual tweets predicts earnings surprises.

Models III and IV in Table 4, Panel A, presents the results from estimating Equation (1) using *FE* as the dependent variable. While *FE* may measure the earnings surprise more accurately than *SUE*, as it reflects more current information, there is a slight (under seven percent) decline in sample size due to the need to use analyst earnings forecast data. The results for *FE* are broadly similar to those for *SUE*. In Model III, the coefficient on *OPI_BAYES* is positive (0.0075) and significant (*t*-statistic = 2.53). Likewise, in Model IV, the coefficient on *OPI_VOCAB* is positive (0.0193) and significant (*t*-statistic = 2.40). Interestingly, the coefficients on the control variables $EXRET_{[-10;-2]}$ and *PRIOR_FE* are significantly positive in both models. While this finding may appear somewhat surprising, it is consistent with findings in prior research indicating that analyst earnings expectations do not fully reflect information in stock prices and that analyst earnings forecast errors are positively serially correlated (see, e.g., Lys and Sohn 1990; Abarbanell 1991). As before, the coefficient on *RP_OPI* is significantly positive in both models, indicating that the aggregate Twitter opinion effect is incremental to opinion from traditional media sources.[16]

[16] A comparison of the coefficients on the control variables shows a broad similarity across the two specifications (*SUE* and *FE*), with a few exceptions. The indicator variables *Q4* and *LOSS* are positively correlated with *SUE*, yet negatively correlated with *FE*. This is a reflection of the univariate correlations displayed in Table 3, Panel B, where *SUE* (*FE*) is positively (negatively) correlated with *Q4* and *LOSS*. To ensure that this does not affect our results, we estimate the regressions after excluding both *Q4* and *LOSS,* and find almost identical results to those tabulated.

Table 4, Panel B, repeats the analysis in Table 4, Panel A, using measures of *OPI* disaggregated between original tweets and dissemination tweets. As in Panel A, Models I and II (III and IV) present results with *SUE* (*FE*) as the dependent variable. In Model I using *OPI_BAYES*, the coefficient on *OPI_ORIG* is insignificant, while the coefficient on *OPI_DISSEM* is positive (0.0272) and significant (*t*-statistic = 3.03). Recall that *OPI_BAYES* is the only measure that considers positive information, which prior research has generally found to be unreliable. This may potentially explain the insignificance of *OPI_ORIG*. Model II repeats the analysis with components of *OPI_VOCAB* and finds that the original tweet component, *OPI_ORIG*, and the dissemination component, *OPI_DISSEM*, are both significantly positively associated with *SUE*. In Model III, the results are essentially similar to these of Model I. In Model IV, however, the coefficient on *OPI_ORIG* is positive (0.0175) and significant (*t*-statistic = 1.82), while the coefficient on *OPI_DISSEM* is insignificant. Within each regression, *F*-tests indicate the coefficients on the *OPI_ORIG* and *OPI_DISSEM* variables are insignificantly different from each other in all specifications. Taken together, these results suggest that the aggregate opinion from individual tweets can help predict earnings, with no statistical difference in the predictive ability between tweets that convey original information and tweets that disseminate existing information.

Table 4, Panel C, repeats the analysis in Table 4, Panel A, decomposing *OPI* between tweets that convey earnings, fundamental, and/or trade-related information (*OPI_FUNDA*) and tweets that contain other information (*OPI_NONFUNDA*). In Model I with *OPI_BAYES*, the coefficient on *OPI_FUNDA* is positive (0.0306) and significant (*t*-statistic = 3.24), while the coefficient on *OPI_NONFUNDA* is insignificant. Results from *F*-tests indicate a significant difference in these coefficients (*p*-value < 0.01). In Model II with *OPI_VOCAB*, the coefficient on *OPI_FUNDA* is positive (0.2763) and significant (*t*-statistic = 11.18), as is the coefficient on

OPI_NONFUNDA (0.0827, *t*-statistic = 3.22). Results from *F*-tests indicate, again, a significant difference in these coefficients (*p*-value < 0.01). In Models III and IV, for both *OPI_BAYES* and *OPI_VOCAB*, the coefficient on the *OPI_FUNDA* component is positive and significant, while the coefficient on the *OPI_NONFUNDA* component is insignificant. The differences in coefficients are, however, insignificant. One way to interpret these results is that tweets specifically related to earnings, fundamentals, and stock trading are more important for predicting earnings than other tweets.[17]

Collectively, the results in Table 4 suggest that the aggregate opinion from individual tweets helps predict earnings. These findings are robust to alternate definitions of both the test variable and the dependent variable, as well as to the inclusion of a multitude of control variables, including a variable reflecting the opinion from traditional media sources. Further, they suggest a dual role for Twitter, both as a source of new information coming from individual users, as well as a means of disseminating existing information. Additionally, the importance of Twitter in predicting future earnings varies depending on the nature of the financial information it conveys; the importance is enhanced when individual tweets contain information directly related to earnings, firm fundamentals, and/or stock trading.

Aggregate Opinion from Individual Tweets and Announcement Returns

We now turn to our second research question: Can the signals extracted from the aggregate opinion from Twitter predict quarterly earnings announcement stock returns? Clearly, if the information about the forthcoming earnings extracted from the aggregate opinion from Twitter is

[17] A comparison of the coefficients on the components of *OPI* across the *SUE* and *FE* specifications yields some interesting and intuitive insights. The coefficients on *OPI_DISSEM* and *OPI_NONFUNDA* are generally significant (insignificant) when *SUE* (*FE*) is the dependent variable. These results are to be expected. Indeed, tweets disseminating existing information or conveying information not directly related to earnings, firm fundamentals, and/or stock trading are not expected to play as much of a role in predicting earnings surprises when surprises are measured using forecasts from analysts, who are considered sophisticated capital market participants, as opposed to mechanical models.

impounded into stock prices in a timely fashion, the answer would be no. Conversely, if the market is slow in reacting to this information, the answer would be yes. To test this question, we examine the association between abnormal stock returns (*EXRET*) in the three days around earnings announcements, -1 to +1, where day 0 is the earning announcement date, and the aggregate Twitter opinion (*OPI*) in a nine-trading-day period leading to the earnings announcement, -10 to -2. As discussed above, we estimate Equation (2) using bootstrapped standard errors clustered by calendar quarter and industry.

Consider first the results in Table 5, Panel A. Model I presents the results using *OPI_BAYES*. The results suggest a positive relation between the aggregate Twitter opinion and abnormal returns around earnings announcements, as the coefficient on *OPI_BAYES* is significantly positive (0.0599, *t*-statistic = 3.69). This positive relation is above and beyond effects shown by prior research to explain the cross-sectional variation in stock returns around earnings announcements (*FE*, $EXRET_{[-10;-2]}$, *ANL*, *INST*, *Q4*, and *LOSS*), as well as for, *RP_OPI*, the effect of information and opinion from traditional media sources. Furthermore, this relation holds for *OPI_VOCAB* as well: the coefficient on *OPI_VOCAB* (Model II) is positive, 0.2360, and significant (*t*-statistic = 2.83). One way to interpret this finding is that the market is slow in reacting to information from Twitter because of investor inattention, high information processing cost, or superior information of Twitter users not yet appreciated by the market.[18]

The economic significance of these findings may be illustrated as follows. The inter-

[18] To help corroborate this interpretation, we analyze whether market participants are immediately reacting to the aggregate Twitter opinion using the following specification:

$$EXRET_{[-10;-2]} = \alpha + \beta_1 * OPI_{[-10;-2]} + \beta_2 * RP\_OPI + \beta_3 * ANL + \beta_4 * INST + \beta_5 * Q4 + \beta_6 * LOSS + \varepsilon \quad (4)$$

where the dependent variable is buy-and-hold abnormal returns in the window [-10;-2] concurrent to the aggregate Twitter opinion. The (untabulated) results show that the association between the aggregate Twitter opinion and concurrent returns is significantly positive for both *OPI_BAYES* and *OPI_VOCAB*, suggesting that investors may be reacting contemporaneously to tweets as they are posted. However, this reaction is only partial, as we find a significantly positive association between $OPI_{[-10;-2]}$ and $EXRET_{[-1;+1]}$.

quartile range of *OPI_BAYES* is 1.568 (0.628 – -0.940). A coefficient on *OPI_BAYES* of 0.0599 thus implies a difference in *EXRET* between companies in the 25th and 75th percentiles of the *OPI_BAYES* distribution of (0.0599*1.568=) 9.4 basis points (bps) per three trading days (approximately 8.2 percent annualized return). Using *OPI_VOCAB*, the difference in *EXRET* is much higher, [0.2360*(0.784 – -0.504)=] 30.4 bps per three trading days (approximately 29.0 percent annualized return). Thus, the predicted earnings announcement returns are not only statistically significant; they are also economically important.

What is the nature of the Twitter information that predicts stock returns? Does it relate to forthcoming earnings, or to information other than earnings that may be relevant to stock valuation (e.g., risk, revenue growth)? To answer this, we augment Equation (2) by including the analyst forecast error of the current quarter *(FE*) as our measure of realized earnings surprise. If the information conveyed by *OPI* is above and beyond earnings realizations, the coefficient on *OPI* will continue to be significantly positive even after controlling for *FE*. Models III and IV present the results using *OPI_BAYES* and *OPI_VOCAB*, respectively, and controlling for *FE*. As expected, *FE* loads strongly, and the adjusted R^2 of the regressions increase substantially, from around 0.2 percent to over 5 percent. Importantly, the *OPI* variables continue to be strongly significant in all specifications. This suggests that the value relevance of the aggregate opinion provided by Twitter for stock returns stems not only from predicting the immediate short-term earnings surprise, but also from other information relevant to stock valuation.

Table 5, Panel B, repeats the analysis in Table 5, Panel A, using measures of *OPI* disaggregated between original tweets (*OPI_ORIG*) and dissemination tweets (*OPI_DISSEM*). In Model I, for *OPI_BAYES*, we find that both *OPI_ORIG* and *OPI_DISSEM* have significantly positive coefficients. In Model II, for *OPI_VOCAB*, we find that the coefficient on *OPI_ORIG* is positive (0.2227) and significant (*t*-statistic = 6.75), while the coefficient on *OPI_DISSEM* is insignificant. Furthermore, results from *F*-tests indicate the coefficients on *OPI_ORIG* and *OPI_DISSEM* are insignificantly different. Hence, consistent with our earnings surprise results reported in Table 4, Panel B, we find that both the original component and the dissemination component of the aggregate Twitter opinion are equally important in explaining earnings announcement returns. In Models III and IV, where we augment Equation (2) by including *FE*, the results are mixed. For *OPI_BAYES* (Model III), we find that *OPI_ORIG* is insignificant, while *OPI_DISSEM* is significantly positive. For *OPI_VOCAB* (Model IV), we find that *OPI_ORIG* is significantly positive, while *OPI_DISSEM* is insignificant. However, in both models, we fail to find a statistically significant difference between the coefficients on *OPI_ORIG* and *OPI_DISSEM*.

Table 5, Panel C, repeats the analysis in Table 5, Panel A, using measures of *OPI* disaggregated between tweets that convey earnings, fundamental, and/or trade-related information (*OPI_FUNDA*) and tweets that provide other information (*OPI_NONFUNDA*). In Models I through III, we find that both *OPI_FUNDA* and *OPI_NONFUNDA* are significantly positive. In Model IV, we find that for *OPI_VOCAB* the coefficient on *OPI_FUNDA* is significantly positive, while the coefficient on *OPI_NONFUNDA* is insignificant. In all specifications, the coefficients on *OPI_FUNDA* and *OPI_NONFUNDA* are insignificantly different from each other. A comparison of the results between Panel C of Table 4 and Panel C of Table 5 presents an interesting contrast. *OPI_FUNDA* appears to matter both for the forecasting of earnings and the market reaction to earnings news. Thus, tweets that contain earnings, fundamental, and/or trade-related information provide information relevant to both earnings as well as stock valuation. *OPI_NONFUNDA*, on the other hand, generally does not predict earnings but is associated with earnings announcement returns, suggesting that it provides information irrelevant for short-term earnings yet still useful for valuation.

Aggregate Opinion from Individual Tweets and the Information Environment

The results so far suggest that the aggregate opinion from individual tweets provide valuable information that can help predict earnings and announcement returns. However, this Twitter effect is unlikely to be uniform across firms. Specifically, firms in strong information environments have numerous alternative sources of information, thus the information on Twitter may have already been conveyed to the market and is likely to be less relevant for predicting returns. Conversely, for firms in weak information environments, the information contained in the aggregate Twitter opinion may not have reached the market yet, and is hence more relevant for predicting returns. We examine this conjecture next.

As discussed above, we employ a proxy for weak information environments, *POORINFO*, which we interact with *OPI* and *RP_OPI*, to allow for a differential effect of the aggregate opinion from Twitter and traditional media across firms in strong and weak information environments.[19] We estimate Equation (3) above using bootstrapped standard errors clustered by calendar quarter and industry. In this equation, if the aggregate Twitter opinion effect is more pronounced in firms surrounded by weak information environments, then $\beta_2 > 0$.

The results are presented in Table 6. Models I and II present the results with *OPI_BAYES* and *OPI_VOCAB*, respectively. Note that in these regressions, the coefficient on *OPI* represents the impact of aggregate Twitter opinion on announcement stock returns for firms in strong information environments, while the coefficient on *OPI*POORINFO* represents the incremental effect of *OPI* on the announcement returns for firms in weak information environments. In both

[19] Out of the 33,114 firm-quarter observations included in each specification in Table 6, 7,414 (25,700) are classified as *POORINFO* = 1 (0).

specifications, the coefficient on *OPI* is significantly positive, indicating that Twitter explains the cross-sectional variation in announcement returns even for firms with strong information environments. Turning to the interaction term, *OPI*POORINFO* has an insignificant coefficient for *OPI_BAYES*. However, for *OPI_VOCAB*, the interaction term *OPI*POORINFO* has a significantly positive coefficient, supporting our conjecture that aggregate Twitter opinion plays a greater role in predicting announcement returns for firms in weak information environments.

The next two models of Table 6 consider the disaggregation of *OPI* into original and dissemination tweets. Model III presents the results using *OPI_BAYES*. For original tweets, the coefficients on the main effect (*OPI_ORIG*) and the interaction term (*OPI_ORIG*POORINFO*) are both insignificant. For dissemination tweets, the main effect (*OPI_DISSEM)* is significantly positive, but the interaction term (*OPI_DISSEM*POORINFO*) is insignificant. Model IV presents the results using *OPI_VOCAB*. For original tweets, the coefficients on *OPI_ORIG* and *OPI_ORIG*POORINFO* are both positive and significant, with the magnitude of the coefficient on the interaction term more than double the magnitude of the coefficient on the main effect. Turning to dissemination tweets, however, the coefficients on both the main effect and the interaction variable are both insignificant. The results in Model IV thus suggest that the incremental predictive ability for firms in weak information environments documented in Model II is driven by original tweets.

The final two models of Table 6 consider the disaggregation of *OPI* into fundamental and non-fundamental tweets. Models V and VI present the results using *OPI_BAYES* and *OPI_VOCAB*, respectively. For fundamental tweets, the main effect (*OPI_FUNDA*) has a significantly positive coefficient in both models, but the coefficient on the interaction term is insignificant. For non-fundamental tweets, the main effect (*OPI_NONFUNDA*) is significant in both models, but the interaction term is insignificant in Model V and significantly positive in Model VI. Finally, turning to traditional media sources, in Models I through VI, the main effect, *RP_OPI*, has an insignificant coefficient, whereas *RP_OPI*POORINFO* has a significantly positive coefficient. This suggests that the aggregate opinion from traditional media sources plays a significantly greater role in predicting announcement returns for firms in weak information environments compared to firms in strong information environments.

To summarize, the results in Table 6 suggest that the importance of Twitter's role as an information source increases for firms in weak information environments, particularly when it conveys original information.

VII. SUPPLEMENTARY TESTS

Size of the Twitter "Crowd"

One of the assumptions underlying the Wisdom of Crowds is that the "crowd" has enough participants such that the noise in individual opinion is diversified away and the "truth" emerges. Indeed, Berg, Forsythe, and Rietz (1997) show that the Iowa electronic prediction markets are more accurate when the markets have more volume, i.e. more individuals conjecturing about the outcome of the election. In the current context, we would expect that the usefulness of the aggregate opinion from Twitter would be increasing in the number of distinct users tweeting about a given stock. To test this, we first partition our sample into two subsamples based on the median number of distinct tweet users per firm-quarter, and then replicate the tests in Table 5.[20]

Panel A of Table 7 presents the results. The results for the subsample of firm-quarter observations with under five distinct users, Models I and II, show that neither *OPI_BAYES* nor

[20] The median number of distinct tweet users per firm-quarter is five. While five may seem a low number to represent a "crowd," for the subsample of at least five distinct users per firm-quarter the mean and median numbers of distinct users per firm-quarter are much larger; 24.7 and 13, respectively.

OPI_VOCAB are significant. Conversely, the results for the subsample of firm-quarter observations with five or more distinct users, Models III and IV, demonstrate that both *OPI_BAYES* and *OPI_VOCAB* have significantly positive coefficients. Taken together, these results suggest, as expected, that the Wisdom of Crowds needs a nontrivial number of distinct users providing their insights for the information to be useful to capital market participants.

Twitter Usage Intensity

Recall that our sample consists of 869,733 tweets from 83,751 distinct users and an average of approximately 10 tweets per user (see Table 2, Panel B). However, not all users are equally active on Twitter. The top one percent of Twitter users (838 distinct users) put out 542,890 tweets in our sample, which represents 62.4 percent of the sample, with these top users tweeting at least 159 times and an average of 647 times. Given that the tweets in our sample all have cashtags, refer to stocks in the *Russell 3000* Index, and are written just prior to quarterly earnings announcements, one can view the top one percent users as the most credible and sophisticated users. To assess the influence of the top users on our findings, we replicate the analysis in Table 5 using two subsamples: one containing tweets only from the top one percent users and one with the remaining tweets.

Panel B of Table 7 presents the results from this supplementary analysis. Models I and II include the subsample of tweets posted by all users other than the top one percent, and Models III and IV focus on the subsample of tweets by the most active one percent of users. Focusing first on *OPI_VOCAB*, the results are nearly indistinguishable between Model II and Model IV, with a significantly positive coefficient on *OPI_VOCAB* of approximately similar magnitude. This indicates that, when using *OPI_VOCAB* as a measure of the aggregate opinion from Twitter, our results are robust across the two types of users. However, the results somewhat change when using *OPI_BAYES*: while Model III still yields a significantly positive coefficient on the opinion variable

(*OPI_BAYES*), its coefficient turns insignificant in Model I. Recall that only *OPI_BAYES* considers positive information, which prior research, in other settings, has shown to be unreliable mainly due to a lack of credibility (e.g., Tetlock 2007; Engelberg 2008; Loughran and McDonald 2011). In light of this finding, one way to interpret the results in Models I and III is that tweets containing positive opinions can convey relevant and credible information to capital market participants, but only when the source of the information is sophisticated. Overall, the results in Table 7, Panel B, suggest that, when the source of the Twitter information is potentially less sophisticated or credible, only negative opinion provides relevant information, whereas when more sophisticated or credible users tweet, their opinion, whether positive or negative, is important for the capital market.

Difference in Opinions between Twitter and Traditional Media

The results in Table 6 above show that the aggregate Twitter opinion plays a greater role in predicting earnings announcement returns for firms in weak information environments. In a similar spirit, we examine whether the predictive ability of the Twitter information is stronger in settings where the aggregate opinion from individual tweets differs greatly from the traditional media opinion. We expect the aggregate Twitter opinion provides more relevant information to help predict announcement returns when this opinion is considerably different from the opinion of the traditional media.

We partition our sample into three subsamples based on the absolute difference between *OPI*, the aggregate Twitter opinion, and *RP_OPI*, the opinion from traditional media sources. Panel C of Table 7 presents the results. We find that the positive relation between the aggregate Twitter opinion and earnings announcement returns is most pronounced when the absolute differences in opinions are the largest. Specifically, in Models I through IV, for the subsamples where the absolute differences in opinions are small or medium, the coefficients on *OPI_BAYES* and *OPI_VOCAB* are insignificant. However, in Models V and VI, for the subsample where the absolute differences in opinions are large, the coefficients on both *OPI_BAYES* and *OPI_VOCAB* are positive and significant: 0.0582 and 0.2558 (*t*-statistics = 4.22 and 2.50), respectively. These results suggest that, as expected, the Twitter information is relevant for predicting announcement returns particularly when the aggregate Twitter opinion differs from the opinion from traditional media sources.

SeekingAlpha Coverage

The analysis, so far, has focused on Twitter among the many social media platforms because of its advantages (e.g., Twitter consists of a diverse and independent set of information providers; short format of tweets; ease of information search with cashtags). However, investors have access to information from other crowdsourced portals, which may also provide information that is value relevant. An example of this is the SeekingAlpha portal, where users share their analyses and recommendation of stocks with each other. Indeed, recent work by Chen et al. (2014) shows that user-generated research reports posted on the SeekingAlpha portal help predict stock returns in several long-term intervals following the report posting date.

To ensure that our results are not confounded by such crowdsourced research, we rerun the regressions in Table 5 after deleting all observations where the firm in question had a report on SeekingAlpha over the same time period [-10;-2] over which *OPI* is measured.[21] Of the 33,114 firm-quarter observations in the returns analysis sample, only 1,901 observations have SeekingAlpha coverage. In Table 8, we thus rerun the regressions in Table 5 with the remaining 31,213 observations, and test whether the relation between our opinion variables and *EXRET* stays robust. As before, we find a strong and positive relation between both measures of aggregate

[21] The results are qualitatively similar if we measure SeekingAlpha coverage over the period [-41;-11].

Twitter opinion and abnormal returns around earnings announcements. Specifically, in Models I and II, the coefficients on *OPI_BAYES* and *OPI_VOCAB* are significantly positive, respectively, 0.0617 and 0.2073 (*t*-statistics = 3.74 and 2.46, respectively). Furthermore, the results presented in Models III through VI using the disaggregated *OPI* measures are very similar to the results in Table 5. This alleviates concerns that information from SeekingAlpha confounds our findings. Still, we note that despite our efforts to control for information and opinion from SeekingAlpha and traditional media sources, we cannot rule out the possibility that the information on Twitter is not wholly new, but rather gleaned by Twitter users from other information outlets that we have failed to consider.

Extending the Twitter Opinion Window

While our primary analyses focus on the short window just leading up to earnings announcements (day -10 to day -2), it is plausible that information measured over a longer horizon might also be relevant to capital market participants. To test this, we measure Twitter opinion over a longer horizon, from day -30 to day -2, labelled as $OPI_{[-30;-2]}$, and include it to our return regression as the test variable. In their respective regressions, both $OPI\_BAYES_{[-30;-2]}$ and $OPI\_VOCAB_{[-30;-2]}$ are positively and significantly associated with $EXRET_{[-1;+1]}$ (the results are not tabulated for parsimony). This suggests that the aggregate Twitter opinion measured over longer-term horizons is relevant to capital market participants.

Additional Sensitivity Tests

As a validity check, we consider three sets of alternate deflators for *OPI_BAYES* and *OPI_VOCAB*. First, we remove the deflators, i.e., we define *OPI_BAYES* as the weighted number of positive tweets less the weighted number of negative tweets, and *OPI_VOCAB* as the single factor from a factor analysis using unscaled measures of number of negative words in tweets. This approach assumes that the opinion conveyed depends on the total number of net positive tweets or negative words in tweets. Second, we scale each of the measures by firm size (log of either total assets or market value of equity). Firm size is a widely-used deflator in market-based accounting research studies, and it implies the opinion depends on tweeting activity per unit of firm size. Third, we scale by the total number of tweets pertaining to the firm in the period [-10;-2], which helps control for Twitter activity across firms and over time. The results, not tabulated for parsimony, are unaltered for all three sets of alternative specifications. That is, we continue to find that aggregate opinion from tweets is associated with earnings and announcement returns, and that this relation is stronger for firms in weak information environments. This increases confidence that our results are not an artifact of our choice of deflator.

VIII. CONCLUSION

The dramatic increase in the use of social media these past few years had a significant impact on the capital market. Firms use social media to communicate with their investor base and, increasingly, individual investors use social media to share information and insights about stocks. We examine whether the aggregate opinion from individual tweets prior to a quarterly earnings announcement—a recurring, price-moving event scrutinized closely by market participants—is useful in predicting a company's quarterly earnings and announcement returns.

We analyze a broad sample of individual tweets written in the nine-trading-day period leading up to the firms' quarterly earnings announcements, in the four-year period 2009–2012. Two alternative measures of aggregate opinion from individual tweets serve as our test variables. We find that the aggregate Twitter opinion helps predict quarterly earnings, after controlling for other determinants of earnings, including aggregate opinion from traditional media sources. We also find that the aggregate Twitter opinion predicts abnormal returns around earnings announcements.

When we decompose our aggregate opinion variables based on whether tweets convey original information or disseminate existing information, we find that both components are important in predicting earnings and announcement returns. Thus, Twitter plays a dual role in the capital market: it serves as a source of new information as well as a vehicle for the dissemination of existing information. We note, however, that this interpretation should be considered with caution due to a potential classification error, and perhaps may serve as a basis for future research to attempt to classify tweets more reliably.

Further, when we decompose the aggregate opinion based on whether tweets convey information related to earnings, firm fundamentals, and stock trading (*OPI_FUNDA*), or other information (*OPI_NONFUNDA)*, we find that only *OPI_FUNDA* is important for predicting quarterly earnings. However, both *OPI_FUNDA* and *OPI_NONFUNDA* are associated with announcement returns. Finally, we generally find that the aggregate Twitter opinion plays a greater role in predicting announcement returns 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 suggest that individuals use social media to share information regarding companies' future prospects for their mutual benefit. Second, our results are important to regulators. Skeptics argue that individuals exploit social media by disseminating misleading and speculative information, and thus call for regulating social media. However, our results show that the Wisdom of Crowds and the value of diversity and independence trump any concerns about the lack of credibility of information on Twitter. In other words, our findings suggest that the information from social media may help investors in their investment decisions, not mislead them. 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. 1991. Do analysts' earnings forecasts incorporate information in prior stock price changes? *Journal of Accounting and Economics* 14: 147–165.

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

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

Azar, P. D., and A. W. Lo. 2016. The wisdom of Twitter crowds: Predicting stock market reactions to FOMC meetings via Twitter feeds. *Journal of Portfolio Management* 42 (5): 123–134.

Ball, R., and E. Bartov. 1996. How naïve is the stock market's use of earnings information? *Journal of Accounting and Economics* 21: 319–337.

Barberis, N., A. Shleifer, and R. Vishny. 1998. A model of investor sentiment. *Journal of Financial Economics* 49: 307–343.

Beaver, W., M. McNichols, and R. Price. 2007. Delisting returns and their effect on accounting-based market anomalies. *Journal of Accounting and Economics* 43: 341–368.

Berg, J., R. Forsythe, and T. Rietz. 1997. What makes markets predict well? Evidence from the Iowa Electronic Markets. In *Understanding Strategic Interaction*: 444–463, Springer Berlin Heidelberg.

Berg, J., R. Forsythe, F. Nelson, and T. Rietz. 2008. Results from a dozen years of election futures markets research. *Handbook of Experimental Economic Results* 1: 742–751.

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

Blankespoor, E., G. Miller, and H. White. 2014. The role of dissemination in market liquidity: Evidence from firms' use of Twitter™. *The Accounting Review* 89: 79–112.

Bollen, J., H. Mao, and X. Zheng. 2011. Twitter mood predicts the stock market. *Journal of Computational Science* 2: 1–8.

Cameron, C., J. Gelbach, and D. Miller. 2011. Robust inference with multi-way clustering. *Journal Business and Economic Statistics* 29: 238–249.

Cameron, C., and D. Miller. 2015. A practitioner's guide to cluster-robust inference. *The Journal of Human Resources* 50: 317–372.

Carhart, M. 1997. On persistence in mutual fund performance. *Journal of Finance* 52: 57–82.

Chen, H., P. De, Y. Hu, and B. Hwang. 2014. Wisdom of crowds: The value of stock opinions transmitted through social media. *Review of Financial Studies* 27: 1367–1403.

Curtis, A., V. Richardson, and R. Schmardebeck. 2016. Investor attention and the pricing of earnings news. *Handbook of Sentiment Analysis in Finance (Chapter 8)*: 212–232.

Da, Z., J. Engelberg, and P. Gao. 2011. In search of attention. *Journal of Finance* 66: 1461–1499.

Das, S., and M. Chen. 2007. Yahoo! for Amazon: Sentiment extraction from small talk on the Web. *Management Science* 53: 1375–1388.

Drake, M., D. Roulstone, and J. Thornock. 2012. Investor information demand: Evidence from Google searches around earnings announcements. *Journal of Accounting Research*, 50: 1001–1040.

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

Hentschel, M., and O. Alonso. 2014. Follow the money: A study of cashtags on Twitter. *First Monday peer-reviewed journal on the Internet* 19(8). Available at http://firstmonday.org/ojs/index.php/fm/article/view/5385/4109#author

Hirschey, M., V. Richardson, and S. Scholz. 2000. Stock price effects of Internet buy-sell recommendations: The Motley Fool case. *Financial Review* 35: 147–174.

Hong, H., J. Kubik, and A. Solomon. 2000. Security analysts' career concerns and herding of earnings forecasts. *Rand Journal of Economics* 31: 121–144.

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

Hu, M., and B. Liu. 2004. Mining and summarizing customer reviews. *Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*.

Jame, R., Johnston, R., Markov, S., and M. Wolfe. 2016. The value of crowdsourced earnings forecasts. *Journal of Accounting Research* 54 (4): 1077-1110.

Jegadeesh, N., and W. Kim. 2010. Do analysts herd? An analysis of recommendations and market reactions. *Review of Financial Studies* 23: 901–937.

Jung, M., J. Naughton, A. Tahoun, and C. Wang. Do firms strategically disseminate? Evidence from corporate use of social media. Unpublished paper, New York University, 2016. Available at http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2588081

Lee, F., A. Hutton, and S. Shu. 2015. The role of social media in the capital market: Evidence from consumer product recalls. *Journal of Accounting Research* 53 (2): 367–404.

Loughran, T., and B. McDonald. 2011. When is a liability not a liability? Textual Analysis, Dictionaries, and 10-Ks. *Journal of Finance* 66: 35–65.

Lys, T., and S. Sohn. 1990. The association between revisions of financial analysts' earnings forecasts and security price changes. *Journal of Accounting and Economics* 13 (4): 341–363.

Mao, Y., W. Wei, B. Wang, and B. Liu. 2012. Correlating S&P 500 stocks with Twitter data. *Proceedings of the First ACM International Workshop on Hot Topics on Interdisciplinary Social Networks*: 69–72.

Moldoveanu, M., and R. Martin. 2009. Diaminds: Decoding the mental habits of successful thinkers. University of Toronto Press.

Narayanan, V., I. Arora, and A. Bhatia. 2013. 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: 194–201.

Ng, J., T. Rusticus, and R. Verdi. 2008. Implications of transaction costs for the post-earnings announcement drift. *Journal of Accounting Research* 46: 661–696.

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

Shumway, T. 1997. The delisting bias in CRSP data. *Journal of Finance* 52: 327–340.

Stevens, D., and A. Williams. 2004. Inefficiency in earnings forecasts: Experimental evidence of reactions to positive vs. negative information. *Experimental Economics* 7: 75–92.

Surowiecki, J. 2004. The wisdom of crowds: Why the many are smarter than the few and how collective wisdom shapes business, economies, societies and nations. Anchor Books.

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

Tumarkin, R., and R. Whitelaw. 2001. News or noise? Internet postings and stock prices. *Financial Analysts Journal* 57: 41–51.

Welch, I. 2000. Herding among security analysts. *Journal of Financial Economics* 58: 369–396.

APPENDIX A
Variable Definitions

Variable	Definition
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.
ASSETS	Total assets (*ATQ*).
EXRET (%)	Buy-and-hold abnormal returns measured using Carhart's (1997) four-factor model for the window specified, where day zero is the quarterly earnings announcement date, multiplied by 100. We measure the buy-and-hold abnormal returns, for firm *i* over three trading days, as follows: $EXRET_{[-1;+1]} = \prod_{t=1;3} (1 + R_{it}) - \prod_{t=1;3} (1 + ER_{it})$ (5) 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. Returns are adjusted for delisting.[22] We compute the daily abnormal returns using 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: $R_{it} - RF_t = a_i + b_i(RMRF_t) + s_i(SMB_t) + h_i(HML_t) + p_i(UMD_t) + e_{it}$ (6) 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 size factor, HML_t is the book-to-market factor, and UMD_t is the momentum factor. We then use the estimated slope coefficients from Equation (6), b_i, s_i, h_i, and p_i, to compute the expected return for firm *i* on day *t* as follows: $ER_{it} = RF_t + b_i(RMRF_t) + s_i(SMB_t) + h_i(HML_t) + p_i(UMD_t)$ (7) *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).
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.
INST	Number of shares held by institutional investors scaled by total shares outstanding as of the quarter end date.
LOSS	Indicator variable equal to one if earnings before extraordinary items (*IBQ*) is strictly negative in the prior quarter, zero otherwise.
MB	Ratio of market value to book value of equity ([*CSHOQ**PRCCQ*]/*CEQQ*).
MVE	Market value of equity (*CSHOQ**PRCCQ*).
OPI_BAYES	Total number of tweets classified as positive less total number of tweets classified as negative during the nine-trading-day window [-10;-2], where day zero is the quarterly earnings announcement date, using an enhanced naïve Bayes classifier developed by Narayanan et al. (2013).[23] Each positive or negative tweet is first weighted by the corresponding probability and by the number of followers of the user {1 + [Log(1 + Number of Followers)]}. The measure is scaled by one plus the sum of the probability levels.

[22] 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, McNichols, and Price 2007). Following Shumway (1997), we set missing performance-related delisting returns to -100 percent.

[23] The classifier identifies a message as positive, neutral, or negative, with a probability between 50 and 100 percent. A demo of this classifier is available at http://sentiment.vivekn.com/, and the program is available at http://sentiment.vivekn.com/docs/api/.

Variable	Definition
OPI_VOCAB	Single factor from a factor analysis using three vocabulary-based measures. The number of words classified as negative in each tweet is first weighted by the number of followers of the user {1 + [Log(1 + Number of Followers)]}. Then, each measure is defined as minus one multiplied by the sum of the weighted number of negative words during the nine-trading-day window [-10;-2], where day zero is the quarterly earnings announcement date, scaled by one plus the number of words classified as either positive or negative. The three measures employ, respectively, the following word lists and exclude words with negations: the Loughran and McDonald (2011) word list, the Harvard Psychosociological Dictionary (i.e., Harvard IV-4 TagNeg H4N) word list, and the Hu and Liu (2004) word list.[24,25]
OPI_ORIG	*OPI* calculated using only tweets classified as conveying original information (see Appendix B). Calculated for both *OPI_BAYES* and *OPI_VOCAB.*
OPI_DISSEM	*OPI* calculated using only tweets classified as disseminating existing information (see Appendix B). Calculated for both *OPI_BAYES* and *OPI_VOCAB.*
OPI_FUNDA	*OPI* calculated using only tweets primarily containing information directly related to earnings, firm fundamentals, and/or stock trading (see Appendix B). Calculated for both *OPI_BAYES* and *OPI_VOCAB.*
OPI_NONFUNDA	*OPI* calculated using only tweets not classified as containing information directly related to earnings, firm fundamentals, and/or stock trading (see Appendix B). Calculated for both *OPI_BAYES* and *OPI_VOCAB.*
POORINFO	Indicator variable equal to one if *AF*, *INST*, and traditional media coverage are all below sample medians in the same calendar quarter, zero otherwise.
Q4	Indicator variable equal to one if the quarter is the fourth fiscal quarter, zero otherwise.
RP_OPI	Total number of traditional news events classified as positive less total number of traditional news events classified as negative during the nine-trading-day window [-10;-2], where day zero is the quarterly earnings announcement date, using the RavenPack database. Each positive or negative traditional news event is weighted by RavenPack's ESS (Event Sentiment Score) rescaled to range between 0 and 1, where higher values indicate stronger sentiment, and the measure is scaled by the sum of the ESS rescaled.
SIZE	Natural logarithm of MVE.
SUE	Standardized unexpected earnings, measured using quarterly diluted earnings per share excluding extraordinary items (*EPSFXQ*) and applying a seasonal random walk with drift model.

[24] Loughran and McDonald (2011) developed several word lists to be used in textual analysis in financial applications. These word lists are available at http://www.nd.edu/~mcdonald/Word_Lists.html.

[25] Hu and Liu (2004) developed comprehensive word lists to be used in opinion mining and sentiment analysis in social media. These word lists are available at https://www.cs.uic.edu/~liub/FBS/sentiment-analysis.html.

APPENDIX B
Classifying Individual Tweets

We classify individual tweets based on two alternative schemes: i) whether tweets convey original information ("*ORIG*" for original) or disseminate existing information using retweets, hyperlinks, or seemingly automatically generated tweets about stock news, stock quotes, or stock analyses ("*DISSEM*" for dissemination), and ii) whether tweets contain information directly related to earnings, firm fundamentals, and/or stock trading ("*FUNDA"* for fundamental), or other information ("*NONFUNDA*" for non-fundamental).

Individual Tweets: Original ("*ORIG*") and Dissemination ("*DISSEM*")

A tweet is considered conveying original information if it meets the following three conditions:

i. It is not a retweet of another user's tweet

We identify whether individual tweets are retweets (i.e., reposted or forwarded messages on Twitter) by screening whether the tweets contain any iteration of the "RT @" symbol. In our sample of 869,733 tweets, we identify 115,453 tweets (13.3 percent) as retweets. Examples of retweets include the following:

RT@ $GS should not be enjoying profits at our expense; they should be as poor as taxpayers are; soon; take away fed toys;

RT @alleyinsider: December Was Biggest Month For Xbox 360 Ever -- Five Years After Launch $MSFT by @MattRosoff http://read.bi/gHWrQ3

ii. It does not include a hyperlink

We identify whether individual tweets contain hyperlinks to external Web pages by screening whether the tweets contain "http." In our sample of 869,733 tweets, we identify 555,079 tweets (63.8 percent) with hyperlinks. Examples of tweets with hyperlinks are:

Best Buy - $BBY April put spreaders active on elevated volatility of 71 into EPS and Outlook http://bit.ly/S3Gwv

$cbi still holding 1/2 position. will add if it hits 11. http://tinyurl.com/ccoq73

iii. It is not a seemingly automatically generated tweet

In a noticeable number of tweets, the user is merely conveying a stock price quote, stock price analysis, or stock-related news. These tweets seem to be automatically generated as they all have a very standard format and contain no additional information. We identify 233,568 tweets (26.9 percent of our sample) with such characteristics. A few examples consist of the following:

$oflx stock quote, 11:13am: 12.99 +1.48 (+12.86%)

$GMCR - Green Mountain Stock Analysis - 10day moving average is rising - http://t.co/473YSMzN

$EBAY News: eBay urges sellers to get political http://t.co/3TsuLqP1 #eBay #News #Political

Tweets meeting the three conditions listed above primarily convey original information. Based on this methodology, we classify 263,394 tweets (30.3 percent of our sample) meeting these requirements and use these tweets to estimate *OPI_ORIG*. We consider the remaining, 606,339 tweets (69.7 percent), as tweets disseminating existing information. We use these tweets to estimate *OPI_DISSEM*. Below are examples of each classification.

Examples of Individual Tweets Conveying Original Information ("*ORIG*")

Tweet
$AA cutting 13,000 employees and selling off business units.
Impressed by the anecdotes coming out about new Yahoo CEO Bartz. She sounds tough and very focused. $yhoo
$GRPN rumoured earnings 5 cents raising Q3 estimates after shopping spree #GRPN
$NFLX holding nicely above $300. showing relative strength now. needs to keep holding for me to stay long
$FCSX did well today

Examples of Individual Tweets Disseminating Existing Information ("*DISSEM*")

Tweet
RT @noodls_sRetail: $GME Stock Pile the Energy Drinks-GameStop to Open More Than 4,400... http://t.co/MffHAdv0
$GME - GameStop Stock Analysis - ATR is bullish - http://t.co/0nsjHOFC
$SVU News: Supervalu cutting more jobs http://t.co/5xdoKfEc #Cutting #Jobs #More
Someone just got a simple quote on $CAS @simplestockqtes http://t.co/q6TlcbTr
RT @jpraab: Am I more excited about the $VRNG verdict or the Pres. election?

Individual Tweets: Fundamental ("*FUNDA*") and Non-Fundamental ("*NONFUNDA*")

After thorough review of more than 100,000 tweets, we created three word lists to capture whether an individual tweet primarily contains information directly related to earnings, firm fundamentals, and/or stock trading.

> The earnings-related information list includes the following words: adjusted, earning, ebit, editda, eps, expense, fiscal, gaap, gain, in the black, in the green, in the red, income, loss, noi, nopat, normalized, oibda, operating, per share, pro forma, profit, proforma, pro-forma, results, revenue, sales, yearend, year-end.
>
> The fundamental information list includes the following words: accounting, acquir, aggressive, asset, balance sheet, boosted, business model, capacity, capital, cash, CDS, charge, compete, competit, conservative, consumer, contract, corporat, covenant, customer, debt, decline, demand, dividend, effective, equity, executive, financial statement, forecast, fraud, gain, goodwill, growth, income statement, industry, inflate, innovati, internal control, inventory, investigat, lawsuit, legal, lever, liquidity, m&a,

margin, miss, obfuscate, overstat, patent, peer, ponzi, produc, profit, pyramid, rating, red flag, reserv, resource, restructur, risk, roll-up, solven, supplier, surprise, takeover, technolog, whisper, writedown, write-down, writeoff, write-off.

The stock trade-related information list includes the following words: after hour, analyst, bear, bought, break, bull, buy, call, climb, close, cover, downgrade, downside, halt, high, invest, long, low, market, move, moving, open, play, position, price, put, quote, rally, resistance, sell, share, short, sold, spike, stock, stop, support, target, trade, trading, tumble, upgrade, upside, valuation, value, volume.

With these lists, we identify 639,405 tweets (73.5 percent of our sample) that contain information directly related to earnings, firm fundamentals, and/or stock trading. We use these tweets to estimate *OPI_FUNDA*. The remaining 230,328 tweets (26.5 percent) are used to estimate *OPI_NONFUNDA*. Below are examples of each classification.

Examples of Individual Tweets with Information Directly Related to Earnings, Firm Fundamentals, and/or Stock Trading ("*FUNDA*")

Tweet
$AYI is a BUY
$GE GE AXIS Development Software Reduces Cost, Risk of High... http://www.noodls.com/view/FAC048EE0A7F2EC127E67A16D489E6785F8CA090
Selling the JAN $BBBY calls (Nude 25s and 30s) ahead of earnings.
Mylan Third Quarter Earnings Sneak Peek http://t.co/BkVHfgRp $MYL #stocks #mkt
Howard told me $SIRI will hit $2.00 after earnings.

Examples of Individual Tweets with Other Information ("*NONFUNDA*")

Tweet
look what they did to $vmw
$PBNY Names New CFO
dimon now joins the other dishonest, scheming bankers who will say anything to delay the nasty truth. charlatans.... $jpm
$GM News: For years, General Motors truck parts have been made at Grede Foundries in St ... http://t.co/XCvQSugr #Been #Foundries #General
RT @ValaAfshar: Gmail has 350,000,000 users and adding 5,000 new businesses every day! http://t.co/0UfWNlfi $GOOG #IT #CIO

APPENDIX C
Measuring Opinion from Individual Tweets: Examples of Output

Vitreous Glass Inc. (VCI), Quarterly earnings announcement date: October 26, 2011

Five tweets in our sample mentioning $VCI between October 12 and October 24, 2011

#	Tweet	Followers	*ORIG/DISSEM*	*FUNDA/NONFUNDA*
1	*$VCI getting demolished now, wait, you think the nightly news can't move markets, think again, fear mongering idiots*	4,540	*ORIG*	*FUNDA*
2	*Simple Moving Average Crossover: stock hitting new low - $VCI - http://t.co/nylq1EXs*	59	*DISSEM*	*FUNDA*
3	*$VCI Valassis Announces Its Third Quarter 2011 Earnings Conference Call http://t.co/gR48OaG1*	59	*DISSEM*	*FUNDA*
4	*Valassis Communications, Earnings Estimate $VCI http://t.co/7u1oxQNC*	16	*DISSEM*	*FUNDA*
5	*Valassis Communications, Earnings Estimate $VCI http://t.co/UJOdmN1l*	17	*DISSEM*	*FUNDA*

OPI_BAYES

#	Result	Probability (%)
1	Negative	86.1
2	Negative	79.0
3	Neutral	51.4
4	Neutral	50.0
5	Neutral	50.0

OPI_BAYES = (-1*0.861*{1+[Log(1+4,540)]} + -1*0.790*{1+[Log(1+59)]})
/ (1+0.861+0.790) = -4.578

OPI_VOCAB

#	Number of Negative / Positive Words					
	Loughran and McDonald		Harvard IV-4		Hu and Liu	
	OPI_A		*OPI_B*		*OPI_C*	
	Neg.	Pos.	Neg.	Pos.	Neg.	Pos.
1	2	0	2	0	2	0
2	0	0	1	0	0	0
3	0	0	0	1	0	0
4	0	0	0	0	0	0
5	0	0	0	0	0	0

OPI_A = -1 * (2*{1+[Log(1+4,540)]}) / (1+2+0) = -6.281

OPI_B = -1 * (2*{1+[Log(1+4,540)]} + 1*{1+[Log(1+59)]}) / (1+3+1) = -4.787

OPI_C = -1 * (2*{1+[Log(1+4,540)]}) / (1+2+0) = -6.281

OPI_VOCAB = single factor using *OPI_A*, *OPI_B*, *OPI_C* = -4.082

Triangle Petroleum Corp. (TPLM), Quarterly earnings announcement date: April 16, 2012

Seven tweets in our sample mentioning $TPLM between March 30 and April 12, 2012

#	Tweet	Followers	*ORIG/ DISSEM*	*FUNDA/ NONFUNDA*
1	*I added more $TPLM in the 6.50's today... developing.*	792	*ORIG*	*NONFUNDA*
2	*@traderstewie $TPLM - keep in mind for strong call in April and significant news in July.*	506	*ORIG*	*FUNDA*
3	*$TPLM red from entry looking to time add spot as small oils out of favor.. still love this co.*	497	*ORIG*	*NONFUNDA*
4	*Triangle Petroleum Announces Fourth Quarter Fiscal Year 2012 Earnings and Conference Call $TPLM #oil #petrol #TFB #OIL* http://t.co/gvJDsjTH	10,740	*DISSEM*	*FUNDA*
5	*@HedgeyeENERGY @traderstewie $TPLM - Adding more in front of earnings next week. Update should paint the path to operatorship near term*	501	*ORIG*	*FUNDA*
6	*$TPLM 200 Day SMA Cross - Price crossed above 200 day SMA (6.1098). Confirmed by volume.*	303	*ORIG*	*FUNDA*
7	*Triangle Petroleum Earnings Preview For Monday (TPLM) www.paid2trade/7014/triangle-petroleum-earnings-preview-monday-tplm $TPLM*	49	*ORIG*	*FUNDA*

OPI_BAYES

#	Result	Probability (%)
1	Positive	73.3
2	Positive	91.8
3	Positive	98.2
4	Neutral	50.7
5	Negative	77.7
6	Positive	64.6
7	Neutral	50.0

$$\begin{aligned} \textit{OPI\_BAYES} = {} & (0.733*\{1+[\mathrm{Log}(1+792)]\} + 0.918*\{1+[\mathrm{Log}(1+506)]\} \\ & + 0.982*\{1+[\mathrm{Log}(1+497)]\} + -1*0.777*\{1+[\mathrm{Log}(1+501)]\} \\ & + 0.646*\{1+[\mathrm{Log}(1+303)]\}) / (1+0.733+0.918+0.982+0.777+0.646) = 3.575 \end{aligned}$$

OPI_VOCAB

#	Number of Negative / Positive Words					
	Loughran and McDonald		Harvard IV-4		Hu and Liu	
	OPI_A		*OPI_B*		*OPI_C*	
	Neg.	Pos.	Neg.	Pos.	Neg.	Pos.
1	0	0	0	0	0	0
2	0	1	1	3	0	2
3	0	0	1	2	0	2
4	0	0	0	1	0	0
5	0	0	1	0	0	0
6	0	0	1	0	0	0
7	0	0	0	0	0	0

OPI_A = *OPI_C* = 0

OPI_B = -1 * (1*{1+[Log(1+506)]} + 1*{1+[Log(1+497)]} + 1*{1+[Log(1+501)]}
+ 1*{1+[Log(1+303)]}) / (1+4+6) = -2.580

OPI_VOCAB = single factor using *OPI_A*, *OPI_B*, *OPI_C* = 0.023

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
Tweets pertaining to a ticker symbol with no generic meaning[a]	869,733	33,186	3,604
Final Sample	**869,733**	**33,186**	**3,604**

[a] The complete list of ticker symbols with generic meaning is: $A, $AH, $AI, $AIR, $ALE, $AM, $AME, $AN, $AP, $B, $BC, $BIG, $C, $CAM, $CASH, $CDS, $D, $DOW, $DV, $EE, $EF, $EL, $END, $FOR, $G, $GDP, $H, $HA, $HAE, $HAR, $HE, $HITT, $HOME, $HOT, $HT, $IM, $IN, $IR, $K, $L, $LIFE, $LOW, $M, $MALL, $MAN, $MTG, $NEWS, $O, $OME, $OMG, $P, $QUAD, $R, $RT, $SIX, $UA, $WAG, $WIN, $X, $Y.

TABLE 2
Tweet Descriptive Statistics

Panel A: Distribution of Tweets by Calendar Quarter

Calendar Quarter	Tweets		Firm-Quarter Observations	
	N	%	N	%
2009, Jan-Mar	3,297	0.38	538	1.62
2009, Apr-Jun	12,298	1.41	1,064	3.21
2009, Jul-Sept	13,228	1.52	1,188	3.58
2009, Oct-Dec	12,850	1.48	1,256	3.79
2010, Jan-Mar	22,444	2.58	1,636	4.93
2010, Apr-Jun	27,747	3.19	1,796	5.41
2010, Jul-Sept	26,786	3.08	2,032	6.12
2010, Oct-Dec	25,601	2.94	2,068	6.23
2011, Jan-Mar	53,920	6.20	2,635	7.94
2011, Apr-Jun	67,398	7.75	2,619	7.89
2011, Jul-Sept	68,424	7.87	2,610	7.86
2011, Oct-Dec	92,408	10.62	2,513	7.57
2012, Jan-Mar	91,231	10.49	2,482	7.48
2012, Apr-Jun	122,578	14.09	2,624	7.91
2012, Jul-Sept	105,456	12.13	3,057	9.21
2012, Oct-Dec	124,067	14.27	3,068	9.25
All	**869,733**	**100.00**	**33,186**	**100.00**

Panel B: Tweet Characteristics

Variable	P1	Q1	Mean	Median	Q3	P99	Std. Dev.
Per Tweet (N=869,733)							
Number of Words	2	10	13	13	17	27	6
Number of Followers of the User	0	20	4,127	78	369	30,076	58,388
Number of Past Posts of the User	0	344	9,351	3,543	10,666	82,794	17,199
Per Twitter User (N=83,751)							
Number of Tweets	1	1	10	1	2	159	99
Per Firm-Quarter (N=33,186):							
Number of Tweets	1	2	26	7	18	251	224
Number of Distinct Users	1	2	14	5	13	111	83

TABLE 2 (continued)

Panel C: Distribution of Tweets based on Fama-French 48-Industry Classification

Industry Group & Description	Tweets		Firm-Quarters		Compustat
	N	%	N	%	%
1: Agriculture	1,865	0.21	96	0.29	0.38
2: Food Products	10,403	1.20	518	1.56	1.35
3: Candy and Soda	3,407	0.39	87	0.26	0.32
4: Alcoholic Beverages	3,012	0.35	106	0.32	0.26
5: Tobacco Products	1,791	0.21	56	0.17	0.10
6: Recreational Products	1,662	0.19	105	0.32	0.57
7: Entertainment	21,680	2.49	380	1.14	1.26
8: Printing and Publishing	2,289	0.26	168	0.51	0.47
9: Consumer Goods	6,173	0.71	351	1.06	1.07
10: Apparel	9,739	1.12	415	1.25	0.95
11: Healthcare	4,532	0.52	478	1.44	1.29
12: Medical Equipment	13,724	1.58	952	2.87	2.82
13: Pharmaceutical Products	73,624	8.47	2,418	7.29	6.77
14: Chemicals	11,827	1.36	700	2.11	1.82
15: Rubber and Plastic Products	860	0.10	137	0.41	0.49
16: Textiles	456	0.05	62	0.19	0.20
17: Construction Materials	4,562	0.53	381	1.15	1.23
18: Construction	5,675	0.65	416	1.25	0.83
19: Steel Works, Etc.	9,064	1.04	415	1.25	1.09
20: Fabricated Products	507	0.06	51	0.15	0.16
21: Machinery	15,619	1.80	954	2.87	2.38
22: Electrical Equipment	6,044	0.70	501	1.51	1.49
23: Automobiles and Trucks	11,289	1.30	466	1.40	1.31
24: Aircraft	3,944	0.45	197	0.59	0.42
25: Shipbuilding, Railroad Equipment	901	0.10	75	0.23	0.16
26: Defense	1,675	0.19	93	0.28	0.16
27: Precious Metals	3,241	0.37	145	0.44	1.53
28: Non-Metallic and Metal Mining	6,223	0.72	219	0.66	1.67
29: Coal	7,414	0.85	153	0.46	0.33
30: Petroleum and Natural Gas	44,640	5.13	1,777	5.35	4.84
31: Utilities	14,972	1.72	940	2.83	3.98
32: Communications	22,110	2.54	848	2.56	3.25
33: Personal Services	4,897	0.56	421	1.27	0.99
34: Business Services	120,976	13.91	3,252	9.80	9.95
35: Computers	140,657	16.17	1,136	3.42	2.84
36: Electronic Equipment	42,299	4.86	1,982	5.97	5.54
37: Measuring and Control Equipment	6,796	0.78	500	1.51	1.62
38: Business Supplies	6,018	0.69	379	1.14	0.84
39: Shipping Containers	882	0.10	85	0.26	0.20
40: Transportation	14,247	1.64	912	2.75	2.75
41: Wholesale	7,069	0.81	773	2.33	2.67
42: Retail	53,394	6.14	1,807	5.45	3.48
43: Restaurants, Hotels, Motels	14,687	1.69	498	1.50	1.32
44: Banking	49,467	5.69	2,461	7.42	10.39
45: Insurance	19,869	2.29	1,206	3.63	2.79
46: Real Estate	1,812	0.21	173	0.52	1.08
47: Trading	48,578	5.59	2,503	7.54	6.21
48: Miscellaneous	13,161	1.51	438	1.32	2.38
All Industries	**869,733**	**100.00**	**33,186**	**100.00**	**100.00**

The sample consists of 869,733 tweets (83,751 distinct users) covering 33,186 firm-quarter observations (3,604 distinct firms), with earnings announcement dates between January 1, 2009 and December 31, 2012.

TABLE 3
Descriptive Statistics

Panel A: Descriptive Statistics for Key Analysis Variables

Variable	P1	Q1	Mean	Median	Q3	P99	Std. Dev.
OPI_BAYES	-5.124	-0.940	-0.099	0.000	0.628	5.093	2.116
OPI_VOCAB	-3.019	-0.504	0.005	0.450	0.784	0.784	0.981
SUE	-16.495	-1.666	-0.151	-0.010	1.666	10.158	3.922
FE (%)	-8.150	-0.094	0.003	0.067	0.287	4.444	1.326
$EXRET_{[-1;+1]}$ (%)	-24.736	-4.054	0.014	-0.017	3.963	26.287	8.158
$EXRET_{[-10;-2]}$ (%)	-21.291	-3.263	0.343	0.155	3.478	28.967	7.303
RP_OPI	-0.673	0.000	0.105	0.000	0.288	0.868	0.319
ASSETS	24	356	8,718	1,382	5,120	185,518	25,167
MVE	34	306	5,298	1,017	3,540	105,108	14,078
SIZE	3.530	5.724	7.030	6.925	8.172	11.563	1.721
MB	0.294	1.167	3.082	1.874	3.270	28.196	3.948
ANL	0.000	1.386	1.895	2.079	2.639	3.466	0.949
INST	0.000	0.440	0.633	0.711	0.872	1.000	0.297
Q4	0.000	0.000	0.227	0.000	0.000	1.000	0.419
LOSS	0.000	0.000	0.267	0.000	1.000	1.000	0.443

TABLE 3 (continued)

Panel B: Correlation Matrix

	OPI_BAYES	*OPI_VOCAB*	*SUE*	*FE*	*EXRET* [-1;+1]	*EXRET* [-10;-2]	*RP_OPI*	*SIZE*	*MB*	*ANL*	*INST*	*Q4*	*LOSS*
OPI_BAYES		0.14^{***}	0.03^{***}	0.01^{**}	0.02^{***}	0.04^{***}	0.02^{***}	-0.02^{***}	0.01	-0.02^{***}	0.00	0.04^{***}	-0.03^{***}
OPI_VOCAB	0.12^{***}		0.08^{***}	0.03^{***}	0.02^{***}	0.00	-0.05^{***}	-0.26^{***}	-0.13^{***}	-0.24^{***}	-0.06^{***}	-0.03^{***}	0.01
SUE	0.02^{***}	0.07^{***}		0.26^{***}	0.14^{***}	0.04^{***}	0.04^{***}	0.01^{**}	0.03^{***}	-0.01	0.00	0.03^{***}	0.02^{***}
FE	0.01^{*}	0.00	0.19^{***}		0.35^{***}	0.06^{***}	0.05^{***}	0.00	-0.01	0.02^{***}	0.03^{***}	-0.02^{***}	-0.03^{***}
EXRET$_{[-1;+1]}$	0.02^{***}	0.03^{***}	0.13^{***}	0.23^{***}		-0.01^{**}	0.01	0.02^{***}	0.00	0.01^{***}	0.03^{***}	0.01^{*}	-0.04^{***}
EXRET$_{[-10;-2]}$	0.04^{***}	0.03^{***}	0.05^{***}	0.04^{***}	-0.01^{*}		0.12^{***}	0.03^{***}	-0.01	0.00	0.01^{*}	0.01^{**}	-0.02^{***}
RP_OPI	0.02^{***}	-0.03^{***}	0.04^{***}	0.03^{***}	0.01	0.13^{***}		0.16^{***}	0.06^{***}	0.15^{***}	0.06^{***}	-0.01^{*}	-0.03^{***}
SIZE	-0.04^{***}	-0.22^{***}	0.01	0.07^{***}	0.01	-0.02^{***}	0.18^{***}		0.25^{***}	0.69^{***}	0.41^{***}	0.01^{**}	-0.35^{***}
MB	0.00	-0.11^{***}	0.01^{**}	0.01	-0.01^{*}	-0.02^{***}	0.03^{***}	0.08^{***}		0.19^{***}	0.11^{***}	0.01^{**}	-0.06^{***}
ANL	-0.03^{***}	-0.19^{***}	-0.01^{**}	0.06^{***}	0.01^{**}	-0.03^{***}	0.14^{***}	0.64^{***}	0.05^{***}		0.50^{***}	0.02^{***}	-0.22^{***}
INST	-0.01^{**}	-0.04^{***}	0.00	0.07^{***}	0.03^{***}	-0.02^{***}	0.08^{***}	0.39^{***}	-0.02^{***}	0.59^{***}		0.03^{***}	-0.22^{***}
Q4	0.04^{***}	-0.04^{***}	0.01^{**}	-0.02^{***}	0.01^{**}	0.01^{**}	-0.01^{*}	0.01^{**}	0.00	0.02^{***}	0.02^{***}		-0.02^{***}
LOSS	-0.02^{***}	0.01^{**}	0.02^{***}	-0.09^{***}	-0.03^{***}	0.01^{*}	-0.03^{***}	-0.35^{***}	0.08^{***}	-0.23^{***}	-0.24^{***}	-0.02^{***}	

The sample consists of 33,186 firm-quarter observations (3,604 distinct firms), with earnings announcement dates between January 1, 2009 and December 31, 2012. See Appendix A 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, and ***,**,* represent statistical significance at p < 0.01, p < 0.05, and p < 0.10 (two-tailed), respectively.

TABLE 4
Earnings Surprises and Twitter Opinion

Panel A: All Tweets

$$ESURP = \alpha + \beta_1{*}OPI + \beta_2{*}PRIOR\_ESURP + \beta_3{*}EXRET_{[-10;-2]} + \beta_4{*}RP\_OPI + \beta_5{*}SIZE + \beta_6{*}MB + \beta_7{*}ANL + \beta_8{*}INST + \beta_9{*}Q4 + \beta_{10}{*}LOSS + \varepsilon$$

Variable	Coefficient *(t-statistic)*			
	ESURP = SUE		*ESURP = FE*	
	BAYES	*VOCAB*	*BAYES*	*VOCAB*
	Model I	Model II	Model III	Model IV
Intercept	-1.0572***	-1.3467***	-0.3084***	-0.3256***
	(-11.03)	*(-13.23)*	*(-5.57)*	*(-5.66)*
OPI	**0.0275*****	**0.3138*****	**0.0075****	**0.0193****
	(2.84)	***(13.98)***	***(2.53)***	***(2.40)***
PRIOR_ESURP	0.2831***	0.2801***	0.1871***	0.1871***
	(40.47)	*(42.91)*	*(10.98)*	*(11.14)*
$EXRET_{[-10;-2]}$	0.0219***	0.0213***	0.0084***	0.0085***
	(6.40)	*(6.66)*	*(4.60)*	*(4.42)*
RP_OPI	0.3545***	0.3465***	0.0582***	0.0585***
	(5.27)	*(5.27)*	*(2.68)*	*(2.72)*
SIZE	0.1114***	0.1448***	0.0242***	0.0260***
	(7.59)	*(9.39)*	*(3.17)*	*(3.32)*
MB	-0.0112**	-0.0045	0.0018	0.0023
	(-2.10)	*(-0.87)*	*(0.85)*	*(1.04)*
ANL	-0.1111***	-0.0709**	0.0099	0.0123
	(-3.69)	*(-2.41)*	*(0.53)*	*(0.65)*
INST	0.1928**	0.0992	0.1975***	0.1918***
	(2.51)	*(1.31)*	*(4.79)*	*(4.73)*
Q4	0.2968***	0.3437***	-0.0924***	-0.0892***
	(6.23)	*(6.99)*	*(-5.02)*	*(-4.85)*
LOSS	0.8547***	0.8801***	-0.0577**	-0.0570**
	(18.21)	*(18.96)*	*(-2.27)*	*(-2.18)*
N	30,815	30,815	28,784	28,784
Adj. R^2 (%)	9.02	9.60	5.18	5.18

TABLE 4 (continued)

Panel B: Original and Dissemination Tweets

$$ESURP = \alpha + \beta_1{*}OPI\_ORIG + \beta_2{*}OPI\_DISSEM + \beta_3{*}PRIOR\_ESURP + \beta_4{*}EXRET_{[-10;-2]} + \beta_5{*}RP\_OPI + \beta_6{*}SIZE + \beta_7{*}MB + \beta_8{*}ANL + \beta_9{*}INST + \beta_{10}{*}Q4 + \beta_{11}{*}LOSS + \varepsilon$$

Variable	Coefficient *(t-statistic)*			
	ESURP = SUE		*ESURP = FE*	
	BAYES	*VOCAB*	*BAYES*	*VOCAB*
	Model I	Model II	Model III	Model IV
Intercept	-1.0587^{***}	-1.3913^{***}	-0.3069^{***}	-0.3321^{***}
	(-11.09)	*(-14.64)*	*(-5.59)*	*(-5.58)*
OPI_ORIG	**0.0001**	**0.1814^{***}**	**0.0050**	**0.0175^{*}**
	(0.01)	***(6.91)***	***(1.07)***	***(1.82)***
OPI_DISSEM	**0.0272^{***}**	**0.1930^{***}**	**0.0056^{**}**	**0.0100**
	(3.03)	***(7.45)***	***(1.98)***	***(1.18)***
PRIOR_ESURP	0.2831^{***}	0.2805^{***}	0.1871^{***}	0.1872^{***}
	(42.40)	*(42.82)*	*(10.84)*	*(10.76)*
$EXRET_{[-10;-2]}$	0.0220^{***}	0.0218^{***}	0.0084^{***}	0.0085^{***}
	(6.72)	*(6.75)*	*(4.51)*	*(4.77)*
RP_OPI	0.3548^{***}	0.3511^{***}	0.0582^{***}	0.0586^{***}
	(5.18)	*(5.24)*	*(2.77)*	*(2.73)*
SIZE	0.1116^{***}	0.1501^{***}	0.0240^{***}	0.0266^{***}
	(7.71)	*(10.44)*	*(3.22)*	*(3.24)*
MB	-0.0112^{**}	-0.0027	0.0018	0.0025
	(-2.03)	*(-0.50)*	*(0.86)*	*(1.21)*
ANL	-0.1117^{***}	-0.0602^{**}	0.0099	0.0141
	(-3.87)	*(-2.10)*	*(0.55)*	*(0.73)*
INST	0.1952^{**}	0.0616	0.1972^{***}	0.1877^{***}
	(2.53)	*(0.80)*	*(4.85)*	*(4.77)*
Q4	0.2963^{***}	0.3431^{***}	-0.0921^{***}	-0.0888^{***}
	(6.21)	*(7.24)*	*(-4.69)*	*(-4.70)*
LOSS	0.8535^{***}	0.8927^{***}	-0.0580^{**}	-0.0553^{**}
	(17.81)	*(18.56)*	*(-2.18)*	*(-2.09)*
N	30,815	30,815	28,784	28,784
Adj. R^2 (%)	9.02	9.61	5.17	5.19
p-value of F-test:				
$\beta_1 = \beta_2$	*0.11*	*0.79*	*0.92*	*0.61*

TABLE 4 (continued)

Panel C: Fundamental and Non-Fundamental Tweets

$$ESURP = \alpha + \beta_1{*}OPI\_FUNDA + \beta_2{*}OPI\_NONFUNDA + \beta_3{*}PRIOR\_ESURP + \beta_4{*}EXRET_{[-10;-2]} + \beta_5{*}RP\_OPI + \beta_6{*}SIZE + \beta_7{*}MB + \beta_8{*}ANL + \beta_9{*}INST + \beta_{10}{*}Q4 + \beta_{11}{*}LOSS + \varepsilon$$

Variable	Coefficient (*t-statistic*)			
	ESURP = SUE		*ESURP = FE*	
	BAYES	*VOCAB*	*BAYES*	*VOCAB*
	Model I	Model II	Model III	Model IV
Intercept	-1.0614***	-1.3898***	-0.3068***	-0.3308***
	(-11.12)	*(-14.48)*	*(-5.50)*	*(-5.47)*
OPI_FUNDA	**0.0306*** **	**0.2763*** **	**0.0071** **	**0.0159* **
	(3.24)	***(11.18)***	***(2.37)***	***(1.96)***
OPI_NONFUNDA	**-0.0175**	**0.0827*** **	**0.0047**	**0.0091**
	(-1.27)	***(3.22)***	***(1.14)***	***(1.04)***
PRIOR_ESURP	0.2831***	0.2804***	0.1871***	0.1871***
	(42.74)	*(41.41)*	*(10.65)*	*(10.80)*
$EXRET_{[-10;-2]}$	0.0219***	0.0216***	0.0084***	0.0085***
	(6.65)	*(6.60)*	*(4.52)*	*(4.56)*
RP_OPI	0.3589***	0.3510***	0.0577***	0.0590***
	(5.26)	*(5.27)*	*(2.78)*	*(2.74)*
SIZE	0.1125***	0.1508***	0.0239***	0.0267***
	(7.54)	*(10.49)*	*(3.13)*	*(3.32)*
MB	-0.0112**	-0.0035	0.0018	0.0024
	(-2.10)	*(-0.66)*	*(0.82)*	*(1.13)*
ANL	-0.1111***	-0.0646**	0.0099	0.0130
	(-3.93)	*(-2.24)*	*(0.54)*	*(0.68)*
INST	0.1951**	0.0715	0.1976***	0.1891***
	(2.55)	*(0.94)*	*(4.90)*	*(4.69)*
Q4	0.2996***	0.3421***	-0.0923***	-0.0892***
	(6.37)	*(6.96)*	*(-4.91)*	*(-4.92)*
LOSS	0.8535***	0.8899***	-0.0576**	-0.0560**
	(17.54)	*(18.99)*	*(-2.26)*	*(-2.25)*
N	30,815	30,815	28,784	28,784
Adj. R^2 (%)	9.03	9.61	5.18	5.18
p-value of F-test:				
$\beta_1 = \beta_2$	*<0.01*	*<0.01*	*0.65*	*0.62*

This table presents the results from the regressions presented in each panel and estimated using bootstrapped standard errors clustered by firm. The sample consists of 33,186 firm-quarter observations (3,604 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 variables of interest. ***,**,* represent statistical significance at $p < 0.01$, $p < 0.05$, and $p < 0.10$ (two-tailed), respectively. See Appendix A for variable definitions. To mitigate the influence of outliers, all continuous variables are winsorized at the 1st and 99th percentiles.

TABLE 5
Abnormal Stock Returns around Earnings Announcements and Twitter Opinion

Panel A: All Tweets

$$EXRET_{[-1;+1]} = \alpha + \beta_1*OPI + \beta_2*FE + \beta_3*EXRET_{[-10;-2]} + \beta_4*RP\_OPI + \beta_5*ANL + \beta_6*INST + \beta_7*Q4 + \beta_8*LOSS + \varepsilon$$

Variable	Coefficient (*t-statistic*)			
	BAYES	*VOCAB*	*BAYES*	*VOCAB*
	Model I	Model II	Model III	Model IV
Intercept	-0.2146**	-0.2878***	0.3298*	0.2469
	(-2.38)	*(-3.10)*	*(1.95)*	*(1.36)*
OPI	**0.0599*****	**0.2360*****	**0.0532*****	**0.1690***
	(3.69)	***(2.83)***	***(4.06)***	***(1.85)***
FE			1.3922***	1.3921***
			(10.54)	*(10.51)*
$EXRET_{[-10;-2]}$	-0.0127	-0.0129*	-0.0225**	-0.0225**
	(-1.64)	*(-1.83)*	*(-2.34)*	*(-2.41)*
RP_OPI	0.1633	0.1770	0.0554	0.0646
	(1.18)	*(1.44)*	*(0.39)*	*(0.41)*
ANL	-0.1176	-0.0637	-0.2810***	-0.2333**
	(-1.56)	*(-0.85)*	*(-2.84)*	*(-2.42)*
INST	0.8296***	0.7566***	0.3958**	0.3543*
	(3.38)	*(3.14)*	*(2.08)*	*(1.87)*
Q4	0.1895	0.2240	0.3778***	0.4032***
	(1.15)	*(1.16)*	*(2.81)*	*(2.65)*
LOSS	-0.4554**	-0.4524**	-0.0372	-0.0372
	(-2.24)	*(-2.47)*	*(-0.12)*	*(-0.12)*
N	33,114	33,114	29,388	29,388
Adj. R^2 (%)	0.18	0.23	5.29	5.31

TABLE 5 (continued)

Panel B: Original and Dissemination Tweets

$$EXRET_{[-1;+1]} = \alpha + \beta_1{*}OPI\_ORIG + \beta_2{*}OPI\_DISSEM + \beta_3{*}FE + \beta_4{*}EXRET_{[-10;-2]} + \beta_5{*}RP\_OPI + \beta_6{*}ANL + \beta_7{*}INST + \beta_8{*}Q4 + \beta_9{*}LOSS + \varepsilon$$

Variable	Coefficient *(t-statistic)*			
	BAYES	*VOCAB*	*BAYES*	*VOCAB*
	Model I	Model II	Model III	Model IV
Intercept	-0.2142**	-0.3065***	0.3288*	0.2195
	(-2.48)	*(-2.95)*	*(1.72)*	*(1.19)*
OPI_ORIG	**0.0348****	**0.2227*****	**0.0169**	**0.1570*****
	(2.55)	***(6.75)***	***(0.82)***	***(4.40)***
OPI_DISSEM	**0.0547*****	**0.1038**	**0.0559*****	**0.0759**
	(4.45)	***(1.37)***	***(3.92)***	***(0.92)***
FE			1.3922***	1.3915***
			(10.29)	*(9.85)*
$EXRET_{[-10;-2]}$	-0.0128*	-0.0125*	-0.0225**	-0.0221**
	(-1.85)	*(-1.72)*	*(-2.19)*	*(-2.55)*
RP_OPI	0.1618	0.1821	0.0540	0.0680
	(1.24)	*(1.45)*	*(0.37)*	*(0.45)*
ANL	-0.1186*	-0.0396	-0.2815***	-0.2116**
	(-1.76)	*(-0.48)*	*(-2.80)*	*(-2.16)*
INST	0.8295***	0.7026***	0.3987**	0.3207*
	(3.41)	*(2.76)*	*(1.99)*	*(1.72)*
Q4	0.1893	0.2283	0.3764***	0.4059***
	(1.09)	*(1.19)*	*(2.77)*	*(2.59)*
LOSS	-0.4557**	-0.4339**	-0.0380	-0.0246
	(-2.29)	*(-2.37)*	*(-0.12)*	*(-0.08)*
N	33,114	33,114	29,388	29,388
Adj. R^2 (%)	0.18	0.26	5.29	5.33
p-value of F-test: $\beta_1 = \beta_2$	*0.62*	*0.16*	*0.33*	*0.36*

TABLE 5 (continued)

Panel C: Fundamental and Non-Fundamental Tweets

$$EXRET_{[-1;+1]} = \alpha + \beta_1 * OPI\_FUNDA + \beta_2 * OPI\_NONFUNDA + \beta_3 * FE + \beta_4 * EXRET_{[-10;-2]} + \beta_5 * RP\_OPI + \beta_6 * ANL + \beta_7 * INST + \beta_8 * Q4 + \beta_9 * LOSS + \varepsilon$$

Variable	Coefficient *(t-statistic)*			
	BAYES	*VOCAB*	*BAYES*	*VOCAB*
	Model I	Model II	Model III	Model IV
Intercept	-0.2140^{**}	-0.2989^{***}	0.3358^{*}	0.2242
	(-2.36)	*(-3.18)*	*(1.92)*	*(1.15)*
OPI_FUNDA	**0.0467^{**}**	**0.1745^{**}**	**0.0414^{**}**	**0.1366^{*}**
	(2.52)	***(2.05)***	***(2.21)***	***(1.70)***
OPI_NONFUNDA	**0.0619^{***}**	**0.1497^{***}**	**0.0562^{***}**	**0.0929**
	(4.18)	***(2.68)***	***(3.89)***	***(1.55)***
FE			1.3920^{***}	1.3918^{***}
			(10.35)	*(10.37)*
$EXRET_{[-10;-2]}$	-0.0129^{*}	-0.0129^{*}	-0.0227^{**}	-0.0224^{**}
	(-1.86)	*(-1.75)*	*(-2.40)*	*(-2.34)*
RP_OPI	0.1536	0.1913	0.0462	0.0735
	(1.20)	*(1.63)*	*(0.32)*	*(0.48)*
ANL	-0.1220^{*}	-0.0454	-0.2865^{***}	-0.2156^{**}
	(-1.73)	*(-0.59)*	*(-2.88)*	*(-2.14)*
INST	0.8294^{***}	0.7122^{***}	0.3935^{*}	0.3287^{*}
	(3.42)	*(3.10)*	*(1.92)*	*(1.69)*
Q4	0.1897	0.2242	0.3778^{***}	0.4035^{***}
	(1.11)	*(1.14)*	*(2.74)*	*(2.70)*
LOSS	-0.4517^{**}	-0.4440^{**}	-0.0341	-0.0317
	(-2.43)	*(-2.43)*	*(-0.11)*	*(-0.10)*
N	33,114	33,114	29,388	29,388
Adj. R^2 (%)	0.18	0.25	5.29	5.32
p-value of F-test:				
$\beta_1 = \beta_2$	*0.67*	*0.78*	*0.69*	*0.64*

This table presents the results from the regressions presented in each panel and estimated using bootstrapped standard errors clustered by calendar quarter and industry (using the Fama-French 48-industry classification). The sample consists of 33,186 firm-quarter observations (3,604 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 variables of interest. ***, **, * represent statistical significance at $p < 0.01$, $p < 0.05$, and $p < 0.10$ (two-tailed), respectively. See Appendix A for variable definitions. To mitigate the influence of outliers, all continuous variables are winsorized at the 1st and 99th percentiles.

TABLE 6
Abnormal Stock Returns around Earnings Announcements and Twitter Opinion: Role of the Information Environment

$$EXRET_{[-1;+1]} = \alpha_1 + \alpha_2*POORINFO + \beta_1*OPI_{[-10;-2]} + \beta_2*OPI_{[-10;-2]}\times POORINFO + \beta_3*EXRET_{[-10;-2]} + \beta_4*RP\_OPI + \beta_5*RP\_OPI\times POORINFO + \beta_6*ANL + \beta_7*INST + \beta_8*Q4 + \beta_9*LOSS + \varepsilon$$

Variable	Coefficient *(t-statistic)*					
	BAYES	*VOCAB*	*BAYES*	*VOCAB*	*BAYES*	*VOCAB*
	Model I	Model II	Model III	Model IV	Model V	Model VI
Intercept	-0.1667	-0.2064*	-0.1707	-0.2267	-0.1637	-0.2105
	(-1.26)	*(-1.37)*	*(-1.09)*	*(-1.49)*	*(-1.17)*	*(-1.42)*
POORINFO	-0.0780	-0.1454	-0.0749	-0.1426	-0.0846	-0.1574
	(-0.60)	*(-1.06)*	*(-0.54)*	*(-1.21)*	*(-0.63)*	*(-1.33)*
OPI	**0.0648*****	**0.1957****				
	(4.07)	***(2.37)***				
OPI×POORINFO	**-0.0250**	**0.2144****				
	(-0.66)	***(2.10)***				
OPI_ORIG			**0.0319**	**0.1565*****		
			(1.20)	***(4.48)***		
OPI_ORIG×POORINFO			**0.0157**	**0.3626****		
			(0.15)	***(2.17)***		
OPI_DISSEM			**0.0659*****	**0.1160**		
			(6.62)	***(1.28)***		
OPI_DISSEM×POORINFO			**-0.0586**	**-0.0544**		
			(-0.90)	***(-0.69)***		
OPI_FUNDA					**0.0546*****	**0.1530***
					(2.58)	***(1.73)***
OPI_FUNDA×POORINFO					**-0.0415**	**0.1095**
					(-1.16)	***(0.90)***
OPI_NONFUNDA					**0.0604*****	**0.1112***
					(2.92)	***(1.82)***
OPI_NONFUNDA×POORINFO					**0.0111**	**0.2341***
					(0.13)	***(1.87)***
$EXRET_{[-10;-2]}$	-0.0127*	-0.0129*	-0.0129	-0.0125*	-0.0129*	-0.0130
	(-1.69)	*(-1.84)*	*(-1.64)*	*(-1.78)*	*(-1.79)*	*(-1.61)*
RP_OPI	0.0914	0.1046	0.0895	0.1095	0.0814	0.1158
	(0.63)	*(0.74)*	*(0.65)*	*(0.76)*	*(0.60)*	*(0.90)*
RP_OPI×POORINFO	1.8326**	1.8179***	1.8298**	1.8597***	1.8402***	1.8299***
	(2.53)	*(2.69)*	*(2.49)*	*(2.89)*	*(2.65)*	*(2.63)*
ANL	-0.1238*	-0.0838	-0.1238	-0.0610	-0.1284*	-0.0695
	(-1.72)	*(-1.03)*	*(-1.57)*	*(-0.76)*	*(-1.78)*	*(-0.79)*
INST	0.8012***	0.7204***	0.8049***	0.6713***	0.8005***	0.6772***
	(3.36)	*(2.90)*	*(3.25)*	*(2.74)*	*(3.51)*	*(2.78)*
Q4	0.1911	0.2283	0.1905	0.2322	0.1914	0.2296
	(1.11)	*(1.19)*	*(1.09)*	*(1.27)*	*(1.07)*	*(1.24)*
LOSS	-0.4569**	-0.4445**	-0.4568**	-0.4199**	-0.4528**	-0.4317**
	(-2.33)	*(-2.31)*	*(-2.32)*	*(-2.25)*	*(-2.41)*	*(-2.17)*
N	33,114	33,114	33,114	33,114	33,114	33,114
Adj. R^2 (%)	0.19	0.25	0.19	0.29	0.19	0.28
p-value of F-tests:						
$\beta_{1,ORIG} = \beta_{1,DISSEM}$			*0.42*	*0.68*		
$\beta_{1,ORIG} + \beta_{2,ORIG} = \beta_{1,DISSEM} + \beta_{2,DISSEM}$			*0.71*	*0.03*		
$\beta_{1,FUNDA} = \beta_{1,NONFUNDA}$					*0.88*	*0.64*
$\beta_{1,FUNDA} + \beta_{2,FUNDA} = \beta_{1,NONFUNDA} + \beta_{2,NONFUNDA}$					*0.54*	*0.71*

TABLE 6 (continued)

This table presents the results from the regression estimated using bootstrapped standard errors clustered by calendar quarter and industry (using the Fama-French 48-industry classification). The sample consists of 33,186 firm-quarter observations (3,604 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 variables of interest. ***,**,* represent statistical significance at $p < 0.01$, $p < 0.05$, and $p < 0.10$ (two-tailed), respectively. See Appendix A for variable definitions. To mitigate the influence of outliers, all continuous variables are winsorized at the 1st and 99th percentiles.

TABLE 7
Abnormal Stock Returns around Earnings Announcements and Twitter Opinion: Impact of Twitter User Characteristics

Panel A: Sample Partitioned by Number of Distinct Users Per Firm-Quarter

$$EXRET_{[-1;+1]} = \alpha + \beta_1{*}OPI + \beta_2{*}EXRET_{[-10;-2]} + \beta_3{*}RP\_OPI + \beta_4{*}ANL + \beta_5{*}INST + \beta_6{*}Q4 + \beta_7{*}LOSS + \varepsilon$$

Variable	Coefficient (*t-statistic*)			
	Less than Five Distinct Users		Five or More Distinct Users	
	BAYES	*VOCAB*	*BAYES*	*VOCAB*
	Model I	Model II	Model III	Model IV
Intercept	0.3156**	0.1878	-0.8413***	-0.8580***
	(2.55)	*(1.05)*	*(-3.25)*	*(-3.82)*
OPI	**0.0126**	**0.2758**	**0.0606*****	**0.1272***
	(0.27)	***(1.41)***	***(4.02)***	***(1.68)***
$EXRET_{[-10;-2]}$	0.0036	0.0030	-0.0265***	-0.0263***
	(0.28)	*(0.24)*	*(-3.94)*	*(-3.73)*
RP_OPI	0.2396	0.2243	0.1822	0.1868
	(1.03)	*(0.91)*	*(1.08)*	*(1.02)*
ANL	-0.1974*	-0.1974*	0.0461	0.0781
	(-1.66)	*(-1.70)*	*(0.62)*	*(1.06)*
INST	0.6024	0.5984	0.9479***	0.8985***
	(1.60)	*(1.61)*	*(4.11)*	*(4.04)*
Q4	0.0559	0.0844	0.2497	0.2974
	(0.23)	*(0.32)*	*(1.45)*	*(1.46)*
LOSS	-0.3303**	-0.3360**	-0.5455**	-0.5417**
	(-2.14)	*(-2.17)*	*(-2.09)*	*(-2.11)*
N	15,678	15,678	17,436	17,436
Adj. R^2 (%)	0.04	0.08	0.37	0.37

TABLE 7 (continued)

Panel B: Sample Partitioned by Number of Tweets per Distinct User

$$EXRET_{[-1;+1]} = \alpha + \beta_1{*}OPI + \beta_2{*}EXRET_{[-10;-2]} + \beta_3{*}RP\_OPI + \beta_4{*}ANL + \beta_5{*}INST + \beta_6{*}Q4 + \beta_7{*}LOSS + \varepsilon$$

Variable	Coefficient (*t-statistic*)			
	Excluding Top 1% Users (*Users with Less than 159 Tweets in our Sample*)		Top 1% Users (*Users with More than 159 Tweets in our Sample*)	
	BAYES	*VOCAB*	*BAYES*	*VOCAB*
	Model I	Model II	Model III	Model IV
Intercept	-0.5116***	-0.5553***	-0.2711**	-0.3586***
	(-4.75)	*(-4.25)*	*(-2.27)*	*(-3.11)*
OPI	**-0.0002**	**0.2109*****	**0.0721*****	**0.2623*****
	(-0.02)	***(2.79)***	***(4.54)***	***(2.95)***
$EXRET_{[-10;-2]}$	-0.0153*	-0.0161	-0.0146*	-0.0147*
	(-1.66)	*(-1.64)*	*(-1.88)*	*(-1.92)*
RP_OPI	0.2429**	0.2415**	0.1271	0.1466
	(2.17)	*(2.07)*	*(0.98)*	*(1.08)*
ANL	-0.0846	-0.0438	-0.0883	-0.0264
	(-1.51)	*(-0.70)*	*(-1.04)*	*(-0.31)*
INST	1.0286***	0.9580***	0.7870***	0.6997***
	(3.31)	*(3.12)*	*(3.39)*	*(3.23)*
Q4	0.1130	0.1254	0.2793**	0.3250**
	(0.52)	*(0.54)*	*(2.07)*	*(2.28)*
LOSS	-0.4695**	-0.4605**	-0.4913**	-0.4847**
	(-2.17)	*(-2.25)*	*(-2.20)*	*(-2.23)*
N	20,671	20,671	29,936	29,936
Adj. R^2 (%)	0.20	0.26	0.22	0.28

TABLE 7 (continued)

Panel C: Sample Partitioned by Absolute Difference in Opinions between Twitter and Traditional Media

$$EXRET_{[-1;+1]} = \alpha + \beta_1{*}OPI + \beta_2{*}EXRET_{[-10;-2]} + \beta_3{*}RP\_OPI + \beta_4{*}ANL + \beta_5{*}INST + \beta_6{*}Q4 + \beta_7{*}LOSS + \varepsilon$$

Variable	Coefficient (*t-statistic*)					
	Abs(*OPI – RP_OPI*)					
	Small		Medium		Large	
	BAYES	*VOCAB*	*BAYES*	*VOCAB*	*BAYES*	*VOCAB*
	Model I	Model II	Model III	Model IV	Model V	Model VI
Intercept	-0.3123**	-0.3796***	-0.2751	-0.0872	-0.0745	-0.5097*
	(-2.00)	*(-3.76)*	*(-1.27)*	*(-0.28)*	*(-0.29)*	*(-1.79)*
OPI	**0.3065**	**0.0109**	**0.0176**	**0.2043**	**0.0582*****	**0.2558****
	(1.13)	***(0.04)***	***(0.43)***	***(0.63)***	***(4.22)***	***(2.50)***
$EXRET_{[-10;-2]}$	-0.0208	-0.0108	0.0093	-0.0163	-0.0309***	-0.0115
	(-1.00)	*(-0.74)*	*(3.70)*	*(-0.98)*	*(-3.37)*	*(-1.50)*
RP_OPI	-0.0372	0.4515	0.1462	0.1907	0.2242	0.1915
	(-0.07)	*(1.38)*	*(0.61)*	*(0.59)*	*(0.82)*	*(0.79)*
ANL	-0.1697	-0.1515**	-0.0653	-0.0874	-0.1169*	0.0750
	(-1.32)	*(-2.14)*	*(-0.59)*	*(-0.82)*	*(-1.69)*	*(0.55)*
INST	1.3121***	1.0018***	0.7311*	0.6396*	0.4770*	0.6994**
	(2.65)	*(3.45)*	*(1.91)*	*(1.81)*	*(1.77)*	*(1.98)*
Q4	0.1037	0.3399**	0.1018	0.0838	0.3519**	0.2608
	(0.43)	*(2.33)*	*(0.39)*	*(0.28)*	*(2.03)*	*(0.90)*
LOSS	-0.2712	-0.3983	-0.5395***	-0.4211**	-0.5920***	-0.5206*
	(-1.09)	*(-1.43)*	*(-2.60)*	*(-2.08)*	*(-2.85)*	*(-1.70)*
N	11,025	11,040	11,039	11,969	11,050	10,105
Adj. R^2 (%)	0.19	0.17	0.12	0.08	0.25	0.31

This table presents the results from the regressions presented and estimated using bootstrapped standard errors clustered by calendar quarter and industry (using the Fama-French 48-industry classification). The sample consists of 33,186 firm-quarter observations (3,604 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 variables of interest. ***,**,* represent statistical significance at $p < 0.01$, $p < 0.05$, and $p < 0.10$ (two-tailed), respectively. See Appendix A for variable definitions. To mitigate the influence of outliers, all continuous variables are winsorized at the 1st and 99th percentiles.

TABLE 8
Abnormal Stock Returns Around Earnings Announcements and Twitter Opinion, in Subsample without SeekingAlpha Coverage

$$EXRET_{[-1;+1]} = \alpha + \beta_1{*}OPI + \beta_2{*}EXRET_{[-10;-2]} + \beta_3{*}RP\_OPI + \beta_4{*}ANL + \beta_5{*}INST + \beta_6{*}Q4 + \beta_7{*}LOSS + \varepsilon$$

Variable	Coefficient *(t-statistic)*					
	BAYES	*VOCAB*	*BAYES*	*VOCAB*	*BAYES*	*VOCAB*
	Model I	Model II	Model III	Model IV	Model V	Model VI
Intercept	-0.1948*	-0.2568**	-0.1949*	-0.2729**	-0.1940*	-0.2666***
	(-1.85)	*(-2.31)*	*(-1.73)*	*(-2.47)*	*(-1.87)*	*(-2.72)*
OPI	**0.0617*****	**0.2073****				
	(3.74)	***(2.46)***				
OPI_ORIG			**0.0254****	**0.2080*****		
			(2.05)	***(5.90)***		
OPI_DISSEM			**0.0584*****	**0.0861**		
			(3.84)	***(1.11)***		
OPI_FUNDA					**0.0522****	**0.1538***
					(2.46)	***(1.95)***
OPI_NONFUNDA					**0.0472****	**0.1413****
					(2.54)	***(2.27)***
$EXRET_{[-10;-2]}$	-0.0123	-0.0124	-0.0124*	-0.0119	-0.0125*	-0.0123
	(-1.62)	*(-1.58)*	*(-1.65)*	*(-1.59)*	*(-1.70)*	*(-1.63)*
RP_OPI	0.2039	0.2106	0.2032	0.2116	0.1983	0.2199
	(1.31)	*(1.37)*	*(1.30)*	*(1.34)*	*(1.29)*	*(1.42)*
ANL	-0.0869	-0.0488	-0.0877	-0.0320	-0.0896	-0.0378
	(-1.04)	*(-0.58)*	*(-1.07)*	*(-0.39)*	*(-1.15)*	*(-0.48)*
INST	0.7536***	0.7016***	0.7547***	0.6591***	0.7536***	0.6692***
	(3.13)	*(2.81)*	*(3.08)*	*(2.66)*	*(3.10)*	*(2.75)*
Q4	0.1837	0.2151	0.1829	0.2184	0.1846	0.2149
	(0.97)	*(1.06)*	*(0.96)*	*(1.03)*	*(1.00)*	*(0.99)*
LOSS	-0.4772**	-0.4725**	-0.4782***	-0.4524**	-0.4747**	-0.4618**
	(-2.46)	*(-2.52)*	*(-2.58)*	*(-2.47)*	*(-2.51)*	*(-2.54)*
N	31,213	31,213	31,213	31,213	31,213	31,213
Adj. R^2 (%)	0.18	0.21	0.18	0.24	0.18	0.23
p-value of F-tests:						
$\beta_{1,ORIG} = \beta_{1,DISSEM}$			*0.44*	*0.18*		
$\beta_{1,FUNDA} = \beta_{1,NONFUNDA}$					*0.90*	*0.90*

This table presents the results from the regressions estimated using bootstrapped standard errors clustered by calendar quarter and industry (using the Fama-French 48-industry classification). The sample consists of 31,285 firm-quarter observations (3,600 distinct firms), with earnings announcement dates between January 1, 2009 and December 31, 2012, and no reports on the SeekingAlpha portal in the [-10;-2] window prior to earnings announcements. *t*-statistics are in parenthesis below coefficient estimates. Coefficient estimates and *t*-statistics are bolded for the variables of interest. ***,**,* represent statistical significance at $p < 0.01$, $p < 0.05$, and $p < 0.10$ (two-tailed), respectively. See Appendix A for variable definitions. To mitigate the influence of outliers, all continuous variables are winsorized at the 1st and 99th percentiles.