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

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Abstract

Prior research examines how companies exploit Twitter in communicating with investors, how information in tweets by individuals may be used to predict the stock market as a whole, and how Twitter activity relates to earnings response coefficients (the beta from the returns/earnings regression). In this study, we investigate whether analyzing the aggregate opinion in individual tweets about a company's prospects can predict its earnings and the stock price reaction to them. Our dataset contains 998,495 tweets (covering 34,040 firm-quarters from 3,662 distinct firms) by individuals in the nine-trading-day period leading to firms' quarterly earnings announcements in the four-year period, January 1, 2009 to December 31, 2012. Using four alternative measures of aggregate opinion in individual tweets, we find that the aggregate opinion successfully predicts the company's forthcoming quarterly earnings. We also document a positive association between the aggregate opinion and the immediate abnormal stock price reaction to the quarterly earnings announcement. These findings are more pronounced for firms in weaker information environments (smaller firms with lower analyst following and lower institutional ownership). Finally, we provide evidence that our results are not driven by concurrent information from sources other than Twitter, such as press articles or web portals. Overall, these findings highlight the importance for financial market participants to consider the aggregate information on Twitter when assessing the future prospects and value of companies.

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

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1. Introduction

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

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

By far, the biggest revolution in the dissemination of information on the Internet has taken place with the advent of social media platforms, which allow users to instantaneously post their views about stocks to a wide audience. Of all social media platforms, Twitter specifically stands out as a primary tool used by individuals to share information, given its popularity and ease of use. Indeed, the importance of Twitter as a valuable source of information has not gone unnoticed by practitioners. For example, a recent Fortune article noted that Tashtego, a hedge fund firm based in Boston, was setting up a Social Equities Fund, which will based its investment decisions on sentiment from social media.[1] Also, DataMinr, a startup firm that parses Twitter feeds to generate actionable real-time signals, announced that it had raised over $130 million in financing.[2]

Recently, the academic literature has started studying the role Twitter plays in the capital market. One strand of this recent literature investigates how companies exploit this new channel to communicate with investors. For example, Blankespoor et al. (2014) show that firms can reduce information asymmetry among investors by more broadly disseminating their news by sending market participants links, through Twitter, to press releases provided via traditional disclosure methods. Jung et al. (2015) find that roughly half of S&P 1,500 firms have created either a corporate Twitter account or a Facebook page, with a growing preference for Twitter.[3] Lee et al. (2014) show that firms use social media channels such as Twitter to interact with investors in order to attenuate the negative price reactions to consumer product recalls.

Another strand of this literature investigates whether investor mood derived from analyzing text content of Twitter predicts the overall stock market. Bollen et al. (2011) show that aggregate investor model inferred from the textual analysis of daily Twitter feeds can help predict changes in the Dow Jones index. Similarly, Mao et al. (2012) find that the daily number of tweets that mention S&P 500 stocks is significantly correlated with S&P 500 levels, changes and absolute changes. Finally, a third strand of this literature analyzes how investor activity on Twitter, can influence investor response to earnings news. A contemporaneous study, Curtis et

[1] http://fortune.com/2015/04/02/hedge-fund-twitter/

[2] http://www.wsj.com/articles/tweet-analysis-firm-dataminr-raises-funding-1426564862

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

al. (2014), finds that high levels of Twitter activity by investors are associated with greater sensitivity of earnings announcement returns to earnings surprises (higher beta in the returns/earnings regression), while low levels of Twitter activity are associated with significant post-earnings-announcement drift.

However, the question of whether information on Twitter can help predict a company's future earnings and stock returns has not yet been explored. This study fills this gap in the literature by investigating the following three questions: (1) Does the aggregate opinion in individual tweets regarding a company's prospects predict its quarterly earnings? (2) Does the aggregate opinion predict the stock price reaction to the earnings news? And (3) Does information environment quality surrounding a company explain the cross sectional variation in the predictive ability of the aggregate opinion in individual tweets (if it exists)?

Ex-ante, there are a number of reasons to believe that information on Twitter may be intentionally or unintentionally misleading and thus of limited usefulness for the prediction of firm-level earnings and stock returns. First, the information in Twitter might lack credibility as anyone can set up a Twitter account and tweet anonymously about any stock. Twitter has no mechanism to monitor the information tweeted or to incentivize high quality information. Second, the information in Twitter may be intentionally misleading for the Twitter users' own benefits. Indeed, anecdotal evidence points to several instances of users intentionally misleading markets through false and misleading tweets.[4] Finally, tweets are restricted to a mere 140 characters, in contrast to information from other sources, including other social media platforms. This potentially limits the ability of the sender to convey value-relevant information, or at the very least constrains the sender's ability to provide facts and analyses to support the information.

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

Despite the potential for intentional or unintentional misleading information provided, there are at least four reasons why Twitter might provide value relevant and timely information. First, Twitter allows one to tap into the "*Wisdom of Crowds*." The *Wisdom of Crowds* concept refers to a phenomenon first observed by Sir Francis Galton more than a century ago, that a large group of problem-solvers often makes a better collective prediction than that produced by experts. Secondly, Twitter provides a source of information from a diverse set of individuals. Hong and Page (2004) show analytically that a group of diverse problem solvers can outperform groups of homogenous high-ability problem solvers. Tweets by individuals regarding a firm's future prospects provide a source of information that relies on both a large number as well as a diverse set of information providers. This contrasts sharply with the small number of analysts providing research reports, and their rather homogenous backgrounds in terms of demographics and education (Cohen et al. 2010). Third, users in Twitter are more likely to be independent and less likely to "herd" to the consensus viewpoint, unlike analysts (Jegadeesh and Kim 2010), and in contrast with other social media platforms (e.g., blogs, investing portals, etc.), where a central piece of information is posted and users simply comment on the posting. Finally, Twitter's short format of tweets and ease of information search, using of hashtags (#) and cashtags ($) to designate keywords, make it an ideal medium to share breaking news, in contrast to the longer format and potentially reduced timeliness of research reports or articles.[5]

To study our three research questions, we analyze a broad sample of 998,495 tweets (covering 34,040 firm-quarters from 3,662 distinct Russell 3000 firms), in the nine-trading-day period leading up to the quarterly earnings announcement (days -10 to -2, where day 0 is the

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

earnings announcement day), in which individuals opine on a firm's prospects. The sample spans the four-year period, January 1, 2009 to December 31, 2012.

Briefly, we document three sets of findings. With respect to our first research question, we demonstrate the ability of aggregate opinion in individual tweets regarding a company's prospects just prior to the earnings announcement to predict the company's quarterly earnings. Next, we document a positive association between our measures of aggregate tweet opinion written prior to the earnings announcement and the immediate abnormal stock price reactions to the earnings announcements (second research question). Furthermore, the predicted stock price reaction to aggregate tweet opinion is more pronounced in firms surrounded by weaker information environments, i.e., smaller firms with lower analyst following and lower institutional ownership (third research question). This last finding is expected because the information contained in aggregate individual tweets about firms in weaker information environments is more likely to be relevant for predicting future stock returns. Finally, we provide evidence that our results are not driven by concurrent information sources other than Twitter, such as press articles or reports posted on the SeekingAlpha portal.

Overall, the discovery of this study highlights the importance for capital market participants to consider the nature of information in tweets sent by individuals when assessing the future prospects and value of companies. Our study differs from work on companies using Twitter accounts to communicate with investors in that we investigate tweets specific to a company written by individuals that are either (i) not related in any way to the company they are tweeting about, or (ii) even if they are related to the company (e.g., an employee), they are tweeting on their own behalf using their own personal Twitter account, not on behalf of the company, and their affiliation with the company is unknown. We differ from the work on whether investor mood in general predicts the stock market as a whole in that our analysis is at the firm level with a focus on an important corporate event (earnings announcements). We also differ from the work on the relation between investor social media activity and the earnings response coefficients (the beta from the returns/earnings regression). Unlike this work, which documents a mediating influence of the volume of social media activity on the returns-earnings relationship, our paper focuses on the ability of information gleaned from social media to predict future earnings realizations, as well as the market's upcoming reaction to these earnings. Finally, we differ from recent work focusing on user generated research reports on portals such as SeekingAlpha, as we focus on the broad sample of tweets on Twitter, that are not subject to any controls for quality or remuneration, and on their ability to predict the immediate stock price response to earnings (3-day windows), not the stock price changes in a long period (60-day windows) after an article release date.

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

Second, our results are important to regulators. Skeptics may argue that 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 decision-making. Thus, Twitter can play a role in making the market more efficient by uncovering additional value-relevant information, especially for firms in weak information environments, and regulatory intervention does not seem warranted.

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

2. Research Question and Design

2.1 THE INFORMATIVENESS OF AGGREGATE OPINION IN INDIVIDUAL TWEETS

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

Information on Twitter might be useful for the following four reasons. First, Twitter allows one to tap into the "*Wisdom of Crowds*," a concept that goes back over a century and refers to the phenomenon that the aggregation of information provided by many individuals often results in predictions that are better than those made by any single or a few members of the group, or even experts. One classic example from the turn of the 20th century is Sir Francis Galton's surprising finding that the crowd at a county fair accurately predicted the weight of an ox when their individual guesses were averaged. The crowd's average (or median) prediction was closer to the ox's true weight than the estimates of most crowd members, and even closer than any of the separate estimates made by cattle experts.[6] Similarly, trial by jury can be understood as a manifestation of the *Wisdom of Crowds*, especially when compared to trial by a

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

judge, the single expert.[7] Indeed, a recent paper by Chen et al. (2014), which builds on the *Wisdom of Crowds* notion, shows that user-generated research reports posted on the SeekingAlpha portal help predict stock returns in a 60-day interval following the report posting date.

Second, information derived from Twitter comes from a diverse set of information providers. The value of diversity in decision-making has long been acknowledged. Hong and Page (2004) show analytically that a diverse group of decision makers reaches reliably better decisions than a less diverse group of individuals with superior skills. Moldoveanu and Martin (2010), who refer to this result as the Hong-Page theorem, conclude, "a collection of heterogeneous problem solvers will always beat out a single, expert problem solver."[8] Anecdotal evidence suggests that Twitter has among the most diverse set of users among social media platforms.[9]

Third, as Twitter represents the opinion of ordinary individuals, this information is unlikely to be tainted by the well documented biases and conflicts of interest that plague information from the traditional intermediaries such as financial analysts. Finally, Twitter has been documented as one of the most timely and efficient sources of information about breaking news events (Osborne and Dredze 2014).

Still, 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,

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

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

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

there is extremely little control and monitoring on an open platform such as Twitter.[10] Anyone can open an account and share their opinion, whether it be false, misguided, incorrect or manipulative. Hence, whether or not the aggregate information on Twitter is useful in predicting a company's earnings and stock returns is an open empirical question.

2.2 AGGREGATE OPINION IN INDIVIDUAL TWEETS AND EARNINGS SURPRISES

Our first research question asks: Can the aggregate opinion in individual tweets regarding a company's prospects, expressed by individuals just prior to its earnings announcement, predict the company's earnings? An implication of the *Wisdom of Crowds* concept and the Hong-Page theorem is that the aggregation of opinions provided in individual tweets may result in a more accurate estimate of the forthcoming earnings than the one formed based on analysts. This may be the case because individual tweets reflect opinions of a *large* and *diverse* group of people making *independent* and *timely* assessments of a company's future prospects. If either of these conditions is not met, however, the group may make less accurate earnings forecasts, as small-group judgments tend to be more volatile and extreme, and there is a greater chance that the forecasts will drift towards a misplaced bias. This seems to be the case with financial analysts, who belong to a rather small homogenous group that tend to herd (see, e.g., Welch 2000, Hong et al. 2000), and thus, perhaps not surprisingly, produce inefficient earnings forecasts (see, e.g., Abarbanell 1991, Abarbanell and Bernard 1992, Stevens and Williams 2004). To test our first research question, we estimate the following model:

$$SURP = \alpha + \beta_1 * OPI_{[-10;-2]} + \beta_2 * PRIOR\_SURP + \beta_3 * EXRET_{[-10;-2]} + \beta_4 * SIZE \\ + \beta_5 * MB + \beta_6 * ANL + \beta_7 * INST + \beta_8 * Q4 + \beta_9 * LOSS + \varepsilon \tag{1}$$

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

where the dependent variable, *SURP*, is the market earnings surprise, measured either using prior earnings or using analyst forecasts (discussed below in detail). The test variable, $OPI_{[-10;-2]}$, is the aggregate information about the firm extracted from individual tweets written in the period -10 to -2, where day 0 is the firm's earnings announcement date (more details below). The control variables concern: *PRIOR_SURP*, the lagged earnings surprise from the previous quarter, which is included to control for the well-documented positive autocorrelation in earnings surprises; $EXRET_{[-10;-2]}$, Carhart's (1997) four factor buy-and-hold abnormal returns for the firm over the window [-10;-2], multiplied by 100 (see Section 2.3 for the formal definition of the four factor model and buy-and-hold stock returns), which is included to control for information, other than through Twitter, that may have reached the capital market prior to the earnings release; *SIZE* (firm size), *MB* (market-to-book ratio), *ANL* (number of analysts in the consensus IBES quarterly earnings forecast), *INST* (institutional investor holding), *Q4* (indicator variable for the fourth fiscal quarter), and *LOSS* (indicator variable for past quarterly loss). These last six variables control for effects shown by prior research to explain the cross sectional variation in earnings surprises, and are defined in detail in Appendix I. In Equation (1), the hypothesis that the aggregate opinion in tweets predicts earnings, or more specifically the market earnings surprise, implies $\beta_1 > 0$.

One challenge underlying our research design is to estimate the test variable, *OPI*. Along the lines of prior research, we use textual analysis to quantify the opinion expressed in individual tweets. Since performing textual analysis using any word classification scheme is inherently imprecise (see, e.g., Loughran and McDonald 2011), we measure *OPI* by using four alternative methodologies. The first methodology considers both negative and positive words, while the next three methodologies consider only negative words.[11] Our primary focus is on negative word lists because results in prior research indicate that negative word classifications can be effective in measuring tone, as reflected by significant correlations with other financial variables (e.g., Tetlock 2007, Engelberg 2008, Li 2008).

Our first measure, *OPI1*, is based on the enhanced Naïve Bayes classifier developed by Narayanan et al. (2013). It first classifies each tweet, written during the nine-trading-day window [-10;-2], into either positive, negative, or neutral, and computes its reliability (i.e., confidence level ranges from 0 to 100). Then, each tweet is weighted by its confidence level. Finally, *OPI1* is the difference between the weighted number of positive and negative tweets, scaled by the sum of the confidence levels. Our second measure, *OPI2*, is defined as minus one multiplied by the total number of words classified as negative during the nine-day window [-10;-2], scaled by the number of words classified as either positive or negative, using the word lists developed by Loughran and McDonald (2011), excluding words with negations. The third measure, *OPI3*, is defined as minus one multiplied by the total number of words classified as negative during the nine-day window [-10;-2], scaled by the number of words classified as either positive or negative, using the Harvard IV-4 word lists with inflections and excluding words with negations. Our fourth and final measure, *OPI4*, is defined as minus one multiplied by the total number of words classified as negative during the window [-10;-2], scaled by the number of words classified as either positive or negative, using the word lists developed by Hu and Liu (2004) and excluding words with negations.

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

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

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

2.3 Aggregate Opinion in Individual Tweets and Market Reaction to Earnings

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

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

where, the dependent variable, $EXRET_{[-1;+1]}$, is Carhart's (1997) buy-and-hold abnormal returns for the firm over the three-day window, [-1; +1], multiplied by 100. We measure buy-and-hold abnormal returns, for firm *i* over 3 trading days, as follows:

$$\prod_{t=1,3} (1 + R_{it}) - \prod_{t=1,3} (1 + ER_{it}) \quad (3)$$

where, R_{it} is the daily return for firm *i* on day *t* (*t* = -1, 0, +1), inclusive of dividends and other distributions, and ER_{it} is the expected return on day *t* for that firm. If a firm delists during the return accumulation window, we compute the remaining return by using the CRSP daily delisting return, reinvesting any remaining proceeds in the appropriate benchmark portfolio, and adjusting the corresponding market return to reflect the effect of the delisting return on our measures of expected returns (see Shumway 1997, Beaver et al. 2007).[12]

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

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

where, R_{it} is defined as before, RF_t is the one-month T-bill daily return, $RMRF_t$ is the daily excess return on a value-weighted aggregate equity market proxy, SMB_t is the return on a zero-investment factor mimicking portfolio for size, HML_t is the return on a zero-investment factor mimicking portfolio for book-to-market value of equity, and UMD_t is the return on a zero-investment factor mimicking portfolio for momentum factor.[13]

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

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

Next, $OPI_{[-10;-2]}$, the test variable in Equation (2) capturing the aggregate information at the firm-quarter level extracted from individual tweets written in days -10 to -2, is measured using four alternative methodologies described above. The other five explanatory variables in Equations (2), $EXRET_{[-10;-2]}$, *ANL* (number of analysts in the consensus IBES quarterly earnings forecast), *INST* (institutional investor holding), *Q4* (indicator variable for the fourth fiscal

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

[13] *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).

quarter), and *LOSS* (indicator variable for past quarterly loss), are defined in Appendix I.[14] The first variable controls for momentum in stock returns, and is included to ensure that the effects we attribute to our variable of interest (*OPI*) are not the result of momentum of pre-announcement returns. The other four variables are used to control for effects shown by prior research to explain the cross section variation in stock returns around earnings announcements.

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

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

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

[14] Unlike the earnings surprise regressions, we do not include *SIZE* and *MB* in the return regressions as the dependent variable *EXRET* already controls for size and book-to-market. Results are unaltered if we include these variables as well.

Information environment is a multifaceted and multidimensional concept and likely related to a number of correlated factors such as firm size, analyst following, institutional investment and press coverage. Small firms have weaker information environments with less publicly available information. For example, Piotroski (2000) shows that among value firms (firms with high book-to-market ratios), small firms are more likely to be "forgotten" and consequently mispriced. Similarly, Mohanram (2005) shows evidence consistent with greater mispricing of small firms among growth firms (firms with low book-to-market ratios). Analyst following represents the supply side of information, as analysts are important financial intermediaries specialized in analyzing and disseminating stock-price relevant information to the capital market. Conversely, institutional investment represents the demand side for information.

To isolate instances of weak information environment surrounding a firm, we define an indicator variable called *POORINFO*, which equals one if a firm has below median size, below median analyst following, and below median institutional investment, and zero otherwise. We then rerun our returns regressions by adding an interaction of *POORINFO* with our *OPI* proxies using the following specification:

$$EXRET_{[-1;+1]} = \alpha_1 + \alpha_2 * POORINFO + \beta_1 * OPI_{[-10;-2]} + \beta_2 * OPI_{[-10;-2]} \times POORINFO \\ + \beta_3 * EXRET_{[-10;-2]} + \beta_4 * ANL + \beta_5 * INST + \beta_6 * Q4 + \beta_7 * LOSS + \varepsilon \tag{6}$$

In Equation (6), the coefficient β_1 represents the contribution of *OPI* in predicting stocks returns for firms in strong information environments, whereas the coefficient β_2 represents the incremental contribution of *OPI* in predicting stocks returns for firms in weak information environments (i.e., smaller firms with lower levels of analyst following and institutional investment). Hence, our prediction that the Twitter effect is more pronounced in firms surrounded by weak information environment implies $\beta_2 > 0$.

3. Sample Selection and Data

3.1 SAMPLE SELECTION

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

Table 1 presents the effects of our sample selection process on the sample size. Our initial sample contains 10,894,037 tweets (66,290 firm-quarters from 4,733 unique firms) for Russell 3000 firms. Dropping tweets containing multiple stock symbols reduces the sample to 8,713,182 tweet (61,357 firm-quarters from 4,668 unique firms). We restrict our sample to tweets pertaining only to a single stock symbol to ensure what stock the tweet is referring to. Next, we require that the firm being tweeted about is on Compustat. This requirement further decreases our sample size to 8,674,195 tweets (60,638 firm-quarters from 4,596 unique firms). We then exclude tweets written prior to December 17, 2008 (i.e., ten trading days before January 1, 2009), due to limited Twitter activity and limited use of the cash tag in Twitter prior to 2009. This requirement further reduces the sample to 8,462,761 tweets (54,906 firm-quarters from 4,132 unique firms). Finally, given that our interest is in the predictive ability of tweets written just prior to the earnings release, we eliminate all tweets written outside of our event window, day -10 to day -2. This last requirement results, as expected, in the largest loss of sample observations by far (more than 7 million tweets). Still, our final sample is broad and consists of 998,495 tweets, covering 34,040 firm-quarters from 3,662 distinct Russell 3000 firms.[15]

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

3.2 DISTRIBUTION OF TWITTER ACTIVITY OVER TIME AND ACROSS INDUSTRY

Table 2 presents frequency distributions by calendar quarter (Panel A) and industry (Panel B) of tweets and firm-quarters in our final sample.[16] The data in Panel A indicate there has been a dramatic increase in twitter activity over our sample period. In fact, in our sample the number of tweets per calendar quarter increases more than tenfold from 3,580 tweets in the first quarter of 2009 to 141,025 tweets in the fourth quarter of 2012. This pattern is to be expected; it reflects the increased popularity of social media during our sample period. Likewise, the number of firm-quarters in our sample also increases substantially, from 569 in the first quarter of 2009 to 3,126 in the fourth quarter of 2012.

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

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

3.3 Descriptive Statistics for the Analysis Variables

Panel A of Table 3 presents the descriptive statistics for the analysis variables. Of the four aggregate opinion variables, *OPI1*, the only measure capturing a net positive opinion, appears to show negative skewness with a negative mean (-0.029), but a zero median. This might suggest a "bad-news" bias in tweeting, with investors more likely to share their pessimism on social media rather than their optimism. Our two earnings surprise variables, standardized unexpected earnings (*SUE*) and analyst forecast error (*FE*), appear to differ slightly, with *SUE* having a negative mean (-0.150) and median (-0.012), while *FE* has a negative mean (-0.001 percent) but a positive median (0.067 percent). Our measure of excess stock returns around earnings announcements, *EXRET*, has a small positive mean (0.009 percent) and negative median (-0.023 percent).

The firm size variables (*ASSETS* and *MVE*) suggest that the sample spans firms of all sizes, small, medium, and large. The mean market-to-book ratio (*MB*) is 3.061, suggesting that the sample includes many "growth" and intangible intensive firms. The sample also consists of firms in relatively strong information environments. The mean analyst following (*ANL*) is 1.898, which corresponds to an average of over five analysts, and even the first quartile of *ANL* in the sample (1.386) corresponds to close to three analysts. The mean firm has 63.5 percent of its shares held by institutional investors. Finally, slightly less than a quarter of our sample (22.8 percent) corresponds to earnings announcements of fourth quarter results (*Q4*), while slightly more than a quarter of our sample (26.6 percent) reports a quarterly loss in the previous quarter.

3.4 Correlation Coefficients

Panel B of Table 3 presents the pair-wise correlation coefficients among our analysis variables. Figures above and below the diagonal represent, respectively, Spearman and Pearson correlations. The variables include the four measures of aggregate opinion (*OPI1*, *OPI2*, *OPI3*, and *OPI4*), Carthart four-factor adjusted excess returns around earnings announcements (*EXRET*), earnings surprise (*SUE*), forecast error (*FE*), and the control variables.

As expected, the four opinion measures show positive correlations with each other, and particularly, the three opinion measures based on word lists (*OPI2*, *OPI3*, and *OPI4*). In addition, all four opinion variables, our test variables, show positive correlations with each of our three dependent variables, *SUE*, *FE*, and *EXRET*. This may be viewed as *prima facie* evidence of the predictive ability of the aggregate opinion from individual tweets regarding the firm's future earnings and returns.

Also, as one would expect, both *SUE* and *FE* show positive correlations with each other. All the opinion variables are negatively correlated with size and institutional ownership, and all but one opinion variable are negatively correlated with analyst following. 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 high correlation between size and the market-to-book ratio).

4. Results

4.1 AGGREGATE OPINION IN INDIVIDUAL TWEETS AND EARNINGS SURPRISES

Our first research question pertains to the ability of social media to predict quarterly earnings. Is it possible to predict a company's earnings based on the opinion aggregated from individual tweets regarding the firm in the pre-earnings announcement period? To answer this question, we perform regression tests, where the aggregate opinion from individual tweets is the independent (test) variable, as specified in Equation (1) above. We estimate the regression using four alternative specifications for the aggregate opinion variables (*OPI1*, *OPI2*, *OPI3*, and

OPI4), and cluster standard errors by firm.[17] In addition, we use two alternative measures to calibrate the earnings surprise (*SURP*), the dependent variable. The first is the standardized unexpected earnings (*SUE*), and the second is analyst forecast error (*FE*). The results are displayed in Table 4.

Panel A of Table 4 presents the results from estimating Equation (1), where the dependent variable is *SUE*. Model I reports the results using the first measure of aggregate opinion (*OPI1*) from Narayanan et al. (2013). As the results show, *OPI1* is significantly positive, with a coefficient of 0.2160 (*t*-statistic = 4.71). Model II reports the results using the second measure of aggregate Twitter opinion (*OPI2*) from Loughran and McDonald (2011). Here too, *OPI2* is significantly positive, with a coefficient of 0.4235 (*t*-statistic = 5.05). Model III reports the results for the third measure of Twitter opinion (*OPI3*) using the approach from Tetlock (2007) based on the Harvard psychological dictionary. For Model III as well, *OPI3* is significantly positive, with a coefficient of 0.5009 (*t*-statistic = 5.35). Finally, Model IV reports the results using our final measure of aggregate Twitter opinion (*OPI*4) from Hu and Liu (2004). Here too, *OPI*4 loads significantly with a coefficient of 0.4914 (*t*-statistic = 5.56). Taken together, the results provide consistent support that aggregate opinion from individual tweets predicts earnings surprises.

Panel B of Table 4 presents the results from estimating Equation (1) using *FE* as the dependent variable. Given the need for analyst following data, there is a slight (under 7 percent) decline in sample size. The results are broadly similar to those in Panel A. In Model I, the coefficient on *OPI1* is positive (0.0602) and significant (*t*-statistic = 3.87). Likewise, in Model II, the coefficient on *OPI2* is also positive (0.1585) and significant (*t*-statistic = 4.29). In Model

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

III, we continue to find a significant relationship between forecast error and aggregate Twitter opinion, as the coefficient on *OPI3* is significantly positive (0.1599, *t*-statistic = 4.28). Finally, Model IV confirms that this relationship is significant when we use *OPI4* as our aggregate Twitter opinion variable (0.1044, *t*-statistic = 2.81). Interestingly, $EXRET_{[-10;-2]}$, 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 in all four models for both SUE and FE specifications. This finding, which implies that earnings expectations do not fully reflect information in stock prices, is not surprising, as it has been documented by prior research (see, e.g., Lys and Sohn 1990).

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

4.2 Aggregate Opinion in Individual Tweets and Abnormal Stock Returns around Earnings Announcements

We now turn our attention to our second research question: Can investors profit from the signals extracted from the aggregate opinion in social media? To test this question, we examine the association between abnormal stock returns around earnings announcements and the aggregate Twitter opinion in a nine-trading-day period leading to the earnings announcement, -10 to -2. We measure abnormal stock returns (*EXRET*) as the buy-and-hold returns for the three-day window around earnings announcements -1 to +1, controlling for the four factors from the Carhart (1997) model, which uses the three Fama-French factors (market-premium factor, R_m-R_f, size factor, *SMB*, and book-to-market factor, *HML*) as well as momentum (*UMD*). The regressions are estimated with all four alternative measures of aggregate Twitter opinion and using standard errors clustered by calendar quarter and industry.[18] The results are presented in Table 5.

Model I presents the results using *OPI1* as the opinion variable. The results suggest a positive relationship between aggregate Twitter opinion and abnormal returns around earnings announcements, as the coefficient on *OPI1* is significant and positive (0.2758, *t*-statistic = 3.00). This relationship holds for all alternate measures of opinion: the coefficient on *OPI2* (Model II) is 0.9345 (*t*-statistic = 4.80), on *OPI3* (Model III) is 0.9853 (*t*-statistic = 3.55), and on *OPI4* is 0.7577 (*t*-statistic = 3.23). In addition, the control variable $EXRET_{[-10;-2]}$ is generally insignificant—the only exception is the marginally significant $EXRET_{[-10;-2]}$ (-0.0127, *t*-statistic = -1.69), when *OPI1* is the test variable. This finding implies, as expected, there is little evidence in our sample of weak market inefficiency, and is in contrast to the results in Table 4 above (the dependent variable is earnings surprise), where the coefficient on $EXRET_{[-10;-2]}$ is significant in all specifications.

Overall, the results in Table 5 indicate a robust relationship between aggregate opinion from individual tweets and future stock returns around earnings announcements. This builds on the results from Table 4, as it suggests that not only are there the *Wisdom of Crowds* and the value of diversity effects in our data, but investors can actually benefit from this. To what extent can investors benefit from the information in tweets? The economic significance of the estimated coefficient may be illustrated as follows. The inter-quartile range of *OPI1* is 0.749 (0.350 – -0.399). A coefficient on *OPI1* of 0.2758 thus implies a difference in *EXRET* (abnormal stock returns around earnings announcements) between companies in the 25th and 75th

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

percentiles of the *OPI1* distribution of 20.7 (=0.2758*0.749) basis points (bps) per three trading days (approximately 18 percent annualized return). Using the *OPI*3, the difference in *EXRET* is nearly twice as high, 39.4 (=0.9853*(0.000 – -0.400)) bps per three trading days (approximately 38 percent annualized return). Thus, the predicted earnings announcement returns are not only statistically significant; they are also economically important.

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

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

Recall that we combine three measures for the information environment, firm size, analyst following, and institutional investment into a single proxy called *POORINFO*, which equals one if a firm has below median size, analyst following, and institutional investment compared to all other firms in the same calendar quarter, and zero otherwise. We then interact *POORINFO* with our *OPI* variables using the specification in Equation (6) described earlier. In terms of Equation (6), if the Twitter effect is more pronounced in firms surrounded by weak information environment, then $\beta_2 > 0$.

The results are presented in Table 6. The first column presents the regression results using *OPI1* as the variable of interest. The main effect *OPI* continues to be significantly positive with a coefficient of 0.1968 (*t*-statistic = 2.21). The interaction term *OPI*POORINFO* has a positive but insignificant coefficient of 0.3118 (*t*-statistic = 1.39). The next three column repeats the analysis using *OPI2*, *OPI3*, and *OPI4* as our aggregate twitter opinion variable. In all three specifications, the interaction term, *OPI*POORINFO*, loads strongly and significantly. Specifically, *OPI*POORINFO* for *OPI2*, *OPI3*, and *OPI4* is, respectively, 1.5760 (*t*-statistic = 3.55), 1.4610 (*t*-statistic = 2.81), and 1.5217 (*t*-statistic = 3.46), supporting our conjecture that aggregate twitter opinion plays a greater role in predicting earnings announcement period returns for firms in weaker information environment. The results for the coefficient on *OPI2*, *OPI3*, and *OPI4* are mixed. While the coefficient on *OPI2* is significantly positive 0.5453 (*t*-statistic = 2.57), the one on *OPI3*, 0.5765, is only marginally significant (*t*-statistic = 1.84), and the one on *OPI4*, 0.3873, is insignificant (*t*-statistic = 1.43). Overall, the results in Table 6 suggest that, as expected, the aggregate Twitter opinion effect is more pronounced for companies in weak information environments, but it holds even in firms in strong information environments.

4.4 Robustness Tests

Control for Alternative Sources of Information

While our regressions include a control variable for the market's reaction to information concurrent to the [-10;-2] window leading to the earnings announcement ($EXRET_{[-10,-2]}$), we do not explicitly control for specific types of information. In this section we now run a robustness test to ensure that our results are not driven by information that reaches the capital market through alternate sources. We consider two proxies for alternate sources of information: press coverage, and availability of research reports from the SeekingAlpha portal. We obtain press coverage data from the RavenPack News Analytics database, which provides time-stamped data for all news items disseminated via Dow Jones Newswires. We obtain information on research reports on SeekingAlpha using data from the Chen et al. (2014) paper.[19] We rerun the regressions in Table 5 across partitions based on the extent of availability of alternate information using these two proxies. The results are presented in Table 7.

Panel A of Table 7 considers partitions based on press coverage. We create a measure of press coverage by counting the number of press articles about each company in the window [-10;-2], concurrent to when we measure *OPI*.[20] We rank observations into low and high press coverage subsamples by calendar quarter. We rerun Equation (2) across the two subsamples, and test whether the relationship between our opinion variables and *EXRET* stays robust. The results show that the relationship between all four *OPI* measures and announcement period excess returns is significant for both the low press coverage and high press coverage subsamples.

Panel B of Table 7 considers partitions based on coverage on the SeekingAlpha portal. Specifically, we partition our sample into firms that either have or do not have a report on SeekingAlpha over the same time period [-10;-2] that *OPI* is measured.[21] Again, we rerun Equation (2) across the two subsamples, and test whether the relationship between our opinion variables and *EXRET* stays robust. Of the 33,966 observations in the returns analysis sample, only 1,955 observations had SeekingAlpha coverage. The first four columns present the results for the subsample of firms without SeekingAlpha coverage and find a strong relationship between all 4 *OPI* measures and *EXRET*. The next four columns present the regressions for the firms with SeekingAlpha coverage. The relationship between *OPI* and *EXRET* is strongly significant for *OPI2* with a coefficient of 1.9349 (*t*-statistic = 2.96), marginally significant for *OPI4* (1.4457, *t*-statistic = 1.66), and insignificant for *OPI1* and *OPI3*. The weaker results for

[19] We would like to thank Prof. Byoung-Hyoun Hwang for providing us with SeekingAlpha coverage data.

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

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

the subsample with SeekingAlpha coverage could be the result of a lack of power given the small size of the subsample with coverage on SeekingAlpha. The strong relationship between our *OPI* measures and *EXRET* in the subsample without SeekingAlpha coverage suggests that the relationship shown earlier in Table 5 is not driven by information from alternate sources of information.

In summary, the findings in Table 7 suggest that the relationship between aggregate individual opinion in Twitter and stock returns is not driven by information coming from sources other than Twitter.

ALTERNATIVE SCALARS

Finally, in untabulated robustness tests, we use two sets of alternate scalars to measure our opinion variables. First, we use unscaled measures, i.e., the total number of tweets classified as positive less the total number of tweets classified as negative for *OPI1*, and the number of negative words for *OPI2*, *OPI3*, and *OPI4*, based on their respective word lists. This assumes that opinion depends on the absolute number of informative words in investor tweets in addition to the relative number of informative words. Second, we scale by firm size (log of either total assets or market value of equity). This assumes more tweeting activity for larger firms, and thus controls for this dimension of scale. Our results are unaltered for both sets of alternative specifications. We continue to find that aggregate investor opinion in tweets is associated with future earnings realizations and stock returns around earnings realizations. Further, as before, we continue to find that the relationship between aggregate investor opinion and stock returns around earnings announcements is stronger for firms in weaker information environments. This gives us confidence that the results we present in the paper are not an artifact of our choice to scale (or not scale) by a particular scalar.

5. Conclusions

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

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

In this paper, we examine whether Twitter provides value-relevant information to the market. Specifically, we test whether the aggregate opinion in individual tweets about a firm can help predict the firm's earnings and stock returns around earnings announcements, and whether the ability to predict abnormal returns is greater for firms in weaker information environments. To that end, we analyze a broad sample of 998,495 tweets (covering 34,040 firm-quarters from 3,662 distinct Russell 3000 firms) by individuals opining on a firm's future prospects in the nine-trading-day period leading up to the firms' quarterly earnings announcements. The sample spans the four-year period, January 1, 2009 to December 31, 2012. We use four distinct approaches to create measures of aggregate investor opinion derived from individual tweets (*OPI1*, *OPI2*, *OPI3*, and *OPI4*).

We find that the aggregate information in individual tweets help predict quarterly earnings. Controlling for other determinants of earnings, we find a strong positive association between aggregate investor opinion written prior to the earnings announcement and the ensuing market earnings surprise for all four measures. This is consistent with the *Wisdom of Crowds* concept and the Hong-Page theorem, as individuals' tweets predict earnings more accurately than analysts (experts) do. Next, we find that aggregate investor opinion predicts abnormal returns around earnings announcements, i.e., investors can potentially profit from the information in aggregate Twitter opinion, as this information does not appear to already be impounded in stock prices. Furthermore, the relationship between the aggregate information in tweets and abnormal returns is strongest for firms in the weakest information environments, smaller firms with lower levels of analyst following and lower levels of institutional ownership. This suggests that social media can be a particularly valuable conduit of information for firms in weak information environments. Finally, we provide evidence that our results are not driven by concurrent information from sources other than Twitter, and in particular press articles or reports posted on the SeekingAlpha portal.

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

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

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APPENDIX I

Variable Definitions

Variable	Definition
OPI1	Total number of tweets classified as positive less total number of tweets classified as negative during the trading-day window [-10;-2], where day zero is the quarterly earnings announcement date, using an enhanced Naïve Bayes classifier developed by Narayanan et al. (2013). Each positive or negative tweet is weighted by the corresponding confidence level, and the measure is scaled by the sum of the confidence levels (see description in Appendix II)
OPI2	Minus one multiplied by the total number of words classified as negative during the trading-day window [-10;-2], where day zero is the quarterly earnings announcement date, scaled by the number of words classified as either positive or negative, using the word lists developed by Loughran and McDonald (2011) and excluding words with negations (see description in Appendix II)
OPI3	Minus one multiplied by the total number of words classified as negative during the trading-day window [-10;-2], where day zero is the quarterly earnings announcement date, scaled by the number of words classified as either positive or negative, using the Harvard IV-4 word lists with inflections and excluding words with negations (see description in Appendix II)
OPI4	Minus one multiplied by the total number of words classified as negative during the trading-day window [-10;-2], where day zero is the quarterly earnings announcement date, scaled by the number of words classified as either positive or negative, using the word lists developed by Hu and Liu (2004) and excluding words with negations (see description in Appendix II)
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
SUE	Standardized unexpected earnings, measured using quarterly diluted earnings per share excluding extraordinary items (*EPSFXQ*) and applying a seasonal random walk with drift model
FE (%)	Analyst earnings forecast error, measured as I/B/E/S reported quarterly earnings per share less the latest I/B/E/S consensus analyst quarterly earnings per share forecast just prior to the quarterly earnings announcement date, scaled by stock price as of the forecast date, multiplied by 100
ASSETS	Total assets (*ATQ*)
MVE	Market value of equity (*CSHOQ*PRCCQ*)
SIZE	Natural logarithm of MVE
MB	Ratio of market value to book value of equity ([*CSHOQ*PRCCQ*]/*CEQQ*)
ANL	Natural logarithm of one plus the number of analysts in the latest I/B/E/S consensus analyst quarterly earnings per share forecast prior to the quarter end date
INST	Number of shares held by institutional investors scaled by total shares outstanding as of the quarter end date
Q4	Indicator variable equal to one if the quarter is the fourth fiscal quarter, zero otherwise
LOSS	Indicator variable equal to one if earnings before extraordinary items (*IBQ*) is strictly negative in the prior quarter, zero otherwise
POORINFO	Indicator variable equal to one if *SIZE*, *AF*, and *INST* are all below median at the calendar quarter level, zero otherwise

APPENDIX II
Measuring Opinion in Individual Tweets

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

OPI1

OPI1 is defined as the total number of tweets classified as positive less the total number of tweets classified as negative during the nine-day window [-10;-2], where the classification into positive or negative tweets is based on the enhanced Naïve Bayes classifier developed by Narayanan et al. (2013).[22] Each positive or negative tweet is weighted by the corresponding confidence level, and the measure is scaled by the sum of the confidence levels. The program classifies any type of message (e.g., tweet, review, message from message board, forum, blog, etc.) as positive, neutral, or negative, with a confidence level.

Examples of the output of the classification program

Tweet	Result	Confidence Level (%)
Nice gains out of $HERO today. Holding tight looking for new hod. 3% gains so far	Positive	81.9
$GME Aug 21 calls hitting bids on over 3,500 volume, doesn't look very good ahead of earnings on 8/18	Negative	80.0
After last earnings $AGNC ran to its all time high - next report Monday	Positive	79.8
$JOE can be shorted. Remind me this week to do so...	Negative	64.7

OPI2

OPI2 is defined as minus one multiplied by the total number of words classified as negative during the nine-day window [-10;-2], scaled by the number of words classified as either positive or negative, using the word lists developed by Loughran and McDonald (2011), excluding words with negations. Loughran and McDonald (2011) created several word lists to be used in textual analysis in financial applications.[23]

Examples (emphasis added to show the negative words identified)

Tweet	Number of Negative Words
rumor that $IBM to **layoff** 14,000	1
I think $AAPL (Apple, Inc) will **miss** earnings because the company is doing things that would make #SteveJobs stab himself in the eyes.	1

[22] A demo of this classifier is available at http://sentiment.vivekn.com/, and the program is available at http://sentiment.vivekn.com/docs/api/.

[23] The word lists developed by Loughran and McDonald (2011) are available at http://www.nd.edu/~mcdonald/Word_Lists.html.

$APOL just now **breaking** but will be choppy. If market goes, this will work. If market falters, watch out. Be aware of your **STOPS** always.	2
oh man the las time $txi **postponed** earnings, they **missed** huge. whats this time huge **miss** on earnings or rev, ohhhh manits not pretty	3

OPI3

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

Examples (emphasis added to show the negative words identified)

Tweet	Number of Negative Words
I think $amzn is a potential **short**	1
Earnings estimates on Target for 4Q...may prove a tad **too** high. $TGT #retail $$	1
I like $SWI but i **hate** holding through earnings which are in a few days. I'll buy and **try** to **get** out prior to the earnings on 2/7	3
So much for the **worst** being over for JPMorgan Chase? $JPM down 3% pre-market on NYT report that London Whale "hedging" **loss** may **hit** $9B.	3

OPI4

OPI4 is defined as minus one multiplied by the total number of words classified as negative during the nine-day window [-10;-2], scaled by the number of words classified as either positive or negative, using the word lists developed by Hu and Liu (2004), excluding words with negations. Hu and Liu (2004) created comprehensive word lists to be used in opinion mining and sentiment analysis in social media.[24]

Examples (emphasis added to show the negative words identified)

Tweet	Number of Negative Words
$CMG earnings will be key, stock been bouncing around, huge **downside** potential...	1
Not sure how I feel about the $GOOG **rumors** about Twitter -potential is great, but I also remember Dodgeball, Jaiku, Lively...	1
Sellers in $YELP finally appear. They are **worried** about Nov 5 earnings report and perceived **weakness** in display ads.	2
@nyc_mom $AAPL is **struggling** with Gap **resistance** and S&P with price **resistance**, we're getting overbought, so a pullback is near	3

[24] The word lists developed by Hu and Liu (2004) are available at https://www.cs.uic.edu/~liub/FBS/sentiment-analysis.html.

TABLE 1
Sample Selection

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

TABLE 2, PANEL A
Distribution of Tweets per Calendar Quarter

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

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

TABLE 2, PANEL B
Distribution of Tweets per Industry Group based on Fama-French 48-industry classification

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

TABLE 3
Descriptive Statistics

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

Panel A: Descriptive Statistics

Variable	P1	Q1	Mean	Median	Q3	P99	Std Dev
OPI1	-0.920	-0.399	-0.029	0.000	0.350	0.861	0.439
OPI2	-0.833	-0.400	-0.177	0.000	0.000	0.000	0.258
OPI3	-0.783	-0.400	-0.229	-0.214	0.000	0.000	0.225
OPI4	-0.800	-0.400	-0.208	-0.111	0.000	0.000	0.237
SUE	-16.472	-1.671	-0.150	-0.012	1.667	10.165	3.924
FE (%)	-8.280	-0.095	-0.001	0.067	0.286	4.432	1.337
$EXRET_{[-1;+1]}$ (%)	-24.505	-4.048	0.009	-0.023	3.950	26.154	8.126
$EXRET_{[-10;-2]}$ (%)	-21.233	-3.248	0.337	0.161	3.472	28.589	7.265
ASSETS	25	366	8,841	1,410	5,255	189,079	25,506
MVE	34	310	5,340	1,041	3,597	104,664	14,051
SIZE	3.538	5.737	7.045	6.948	8.188	11.559	1.723
MB	0.293	1.162	3.061	1.865	3.251	27.611	3.893
ANL	0.000	1.386	1.898	2.079	2.639	3.466	0.949
INST	0.000	0.444	0.635	0.714	0.873	1.000	0.296
Q4	0.000	0.000	0.228	0.000	0.000	1.000	0.419
LOSS	0.000	0.000	0.266	0.000	1.000	1.000	0.442

Panel B: Correlation Matrix

	OPI1	*OPI2*	*OPI3*	*OPI4*	*SUE*	*FE*	$EXRET_{[-1;+1]}$	$EXRET_{[-10;-2]}$	*SIZE*	*MB*	*ANL*	*INST*	*Q4*	*LOSS*
OPI1		0.05	0.14	0.14	0.04	0.02	0.02	0.04	-0.01	0.01	-0.01	0.00	0.05	-0.03
OPI2	0.05		0.48	0.58	0.02	0.01	0.03	-0.01	-0.23	-0.13	-0.22	-0.01	-0.02	-0.03
OPI3	0.14	0.45		0.54	0.03	0.01	0.03	0.00	-0.22	-0.09	-0.19	-0.03	-0.02	0.00
OPI4	0.15	0.55	0.52		0.03	0.01	0.02	-0.01	-0.30	-0.12	-0.26	-0.07	0.00	0.01
SUE	0.03	0.02	0.03	0.03		0.26	0.14	0.04	0.01	0.03	-0.01	-0.01	0.03	0.02
FE	0.02	0.02	0.01	0.00	0.19		0.35	0.06	0.01	-0.01	0.02	0.04	-0.02	-0.03
$EXRET_{[-1;+1]}$	0.02	0.03	0.03	0.02	0.13	0.23		-0.01	0.02	0.00	0.01	0.03	0.01	-0.03
$EXRET_{[-10;-2]}$	0.04	0.00	0.00	0.01	0.05	0.05	-0.01		0.03	-0.01	0.00	0.01	0.01	-0.02
SIZE	-0.01	-0.24	-0.22	-0.29	0.01	0.08	0.01	-0.02		0.25	0.69	0.40	0.01	-0.35
MB	0.01	-0.11	-0.08	-0.08	0.01	0.01	-0.01	-0.02	0.08		0.20	0.11	0.01	-0.06
ANL	-0.01	-0.18	-0.16	-0.21	-0.01	0.06	0.01	-0.02	0.64	0.06		0.49	0.02	-0.22
INST	0.01	0.00	-0.02	-0.07	0.00	0.07	0.03	-0.02	0.38	-0.02	0.58		0.03	-0.22
Q4	0.05	-0.02	-0.02	0.00	0.01	-0.02	0.01	0.01	0.01	0.00	0.02	0.02		-0.02
LOSS	-0.03	-0.02	0.00	0.02	0.02	-0.09	-0.03	0.01	-0.35	0.08	-0.22	-0.23	-0.02	

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

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

$$SUE = \alpha + \beta_1 * OPI_{[-10;-2]} + \beta_2 * PRIOR\_SUE + \beta_3 * EXRET_{[-10;-2]} + \beta_4 * SIZE + \beta_5 * MB + \beta_6 * ANL + \beta_7 * INST + \beta_8 * Q4 + \beta_9 * LOSS + \varepsilon$$

Model: (above)

Variable	Expected Sign	Coefficient (*t-statistic*)			
		OPI1	*OPI2*	*OPI3*	*OPI4*
		Model I	Model II	Model III	Model IV
Intercept		-1.1000***	-1.1469***	-1.0913***	-1.1482***
		(-12.01)	*(-12.45)*	*(-11.93)*	*(-12.49)*
OPI $_{[-10;-2]}$	+	**0.2160*****	**0.4235*****	**0.5009*****	**0.4914*****
		(4.71)	***(5.05)***	***(5.35)***	***(5.56)***
PRIOR_SUE		0.2826***	0.2826***	0.2824***	0.2825***
		(42.30)	*(42.32)*	*(42.32)*	*(42.31)*
EXRET $_{[-10;-2]}$		0.0238***	0.0244***	0.0243***	0.0242***
		(7.32)	*(7.49)*	*(7.48)*	*(7.42)*
SIZE		0.1240***	0.1394***	0.1372***	0.1430***
		(8.89)	*(9.78)*	*(9.67)*	*(9.90)*
MB		-0.0117**	-0.0090*	-0.0099*	-0.0099*
		(-2.21)	*(-1.69)*	*(-1.87)*	*(-1.86)*
ANL		-0.1061***	-0.0951***	-0.0968***	-0.0971***
		(-3.73)	*(-3.33)*	*(-3.39)*	*(-3.41)*
INST		0.1732**	0.1263*	0.1385*	0.1464*
		(2.31)	*(1.69)*	*(1.84)*	*(1.95)*
Q4		0.2897***	0.3059***	0.3041***	0.2994***
		(6.21)	*(6.56)*	*(6.52)*	*(6.42)*
LOSS		0.8661***	0.8831***	0.8752***	0.8797***
		(18.34)	*(18.52)*	*(18.47)*	*(18.57)*
N		31,602	31,602	31,602	31,602
Adj. R^2 (%)		8.99	9.01	9.01	9.02

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

Model: $FE = \alpha + \beta_1 * OPI_{[-10;-2]} + \beta_2 * PRIOR\_FE + \beta_3 * EXRET_{[-10;-2]} + \beta_4 * SIZE + \beta_5 * MB + \beta_6 * ANL + \beta_7 * INST + \beta_8 * Q4 + \beta_9 * LOSS + \varepsilon$

Variable	Expected Sign	Coefficient (*t-statistic*)			
		OPI1	*OPI2*	*OPI3*	*OPI4*
		Model I	Model II	Model III	Model IV
Intercept		-0.3109***	-0.3320***	-0.3106***	-0.3229***
		(-5.56)	*(-5.78)*	*(-5.55)*	*(-5.66)*
$OPI_{[-10;-2]}$	+	**0.0602*** **	**0.1585*** **	**0.1599*** **	**0.1044*** **
		(3.87)	***(4.29)***	***(4.28)***	***(2.81)***
PRIOR_FE		0.1782***	0.1781***	0.1782***	0.1780***
		(10.17)	*(10.18)*	*(10.18)*	*(10.16)*
$EXRET_{[-10;-2]}$		0.0093***	0.0095***	0.0095***	0.0095***
		(5.11)	*(5.21)*	*(5.20)*	*(5.17)*
SIZE		0.0253***	0.0310***	0.0294***	0.0292***
		(3.44)	*(4.00)*	*(3.88)*	*(3.80)*
MB		0.0017	0.0027	0.0023	0.0021
		(0.80)	*(1.25)*	*(1.08)*	*(1.00)*
ANL		0.0130	0.0186	0.0170	0.0153
		(0.74)	*(1.05)*	*(0.96)*	*(0.86)*
INST		0.1857***	0.1696***	0.1762***	0.1814***
		(4.62)	*(4.26)*	*(4.40)*	*(4.52)*
Q4		-0.0512***	-0.0461***	-0.0470***	-0.0484***
		(-2.95)	*(-2.66)*	*(-2.71)*	*(-2.79)*
LOSS		-0.0448*	-0.0381	-0.0419*	-0.0429*
		(-1.80)	*(-1.54)*	*(-1.69)*	*(-1.73)*
N		29,050	29,050	29,050	29,050
Adj. R^2 (%)		4.89	4.94	4.92	4.88

TABLE 5
Tweet Opinion and Abnormal Stock Returns around Earnings Announcements

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

Model: $EXRET_{[-1;+1]} = \alpha + \beta_1 * OPI_{[-10;-2]} + \beta_2 * EXRET_{[-10;-2]} + \beta_3 * ANL + \beta_4 * INST + \beta_5 * Q4 + \beta_6 * LOSS + \varepsilon$

Variable	Expected Sign	Coefficient *(t-statistic)*			
		OPI1	*OPI2*	*OPI3*	*OPI4*
		Model I	Model II	Model III	Model IV
Intercept		-0.1986*	-0.1071	-0.0353	-0.1133
		(-1.86)	*(-1.05)*	*(-0.28)*	*(-0.98)*
$\boldsymbol{OPI_{[-10;-2]}}$	+	**0.2758*****	**0.9345*****	**0.9853*****	**0.7577*****
		(3.00)	***(4.80)***	***(3.55)***	***(3.23)***
$EXRET_{[-10;-2]}$		-0.0127*	-0.0119	-0.0120	-0.0122
		(-1.69)	*(-1.60)*	*(-1.60)*	*(-1.63)*
ANL		-0.1135	-0.0481	-0.0633	-0.0665
		(-1.56)	*(-0.69)*	*(-0.89)*	*(-0.95)*
INST		0.8109***	0.7006***	0.7363***	0.7669***
		(3.27)	*(2.82)*	*(2.92)*	*(3.09)*
Q4		0.1816	0.2072	0.2021	0.1931
		(1.12)	*(1.26)*	*(1.23)*	*(1.17)*
LOSS		-0.4465**	-0.4264**	-0.4427**	-0.4465**
		(-2.24)	*(-2.18)*	*(-2.25)*	*(-2.25)*
N		33,966	33,966	33,966	33,966
Adj. R^2 (%)		0.19	0.25	0.24	0.21

TABLE 6
Tweet Opinion, Abnormal Stock Returns around Earnings Announcements, and Level of Information Environment

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

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

Variable	Expected Sign	Coefficient (*t-statistic*)			
		OPI1	*OPI2*	*OPI3*	*OPI4*
		Model I	Model II	Model III	Model IV
Intercept		-0.3325	-0.2680	-0.2178	-0.2768
		(-1.61)	*(-1.31)*	*(-1.05)*	*(-1.30)*
POORINFO		0.1448	0.3315**	0.3869***	0.3328*
		(0.78)	*(2.03)*	*(3.57)*	*(1.76)*
$\boldsymbol{OPI_{[-10;-2]}}$	+	**0.1968****	**0.5453****	**0.5765***	**0.3873**
		(2.21)	***(2.57)***	***(1.84)***	***(1.43)***
$\boldsymbol{OPI_{[-10;-2]}\times POORINFO}$	+	**0.3118**	**1.5760*****	**1.4610*****	**1.5217*****
		(1.39)	***(3.55)***	***(2.81)***	***(3.46)***
$EXRET_{[-10;-2]}$		-0.0128*	-0.0113	-0.0117	-0.0118
		(-1.70)	*(-1.53)*	*(-1.54)*	*(-1.57)*
ANL		-0.0881	-0.0454	-0.0574	-0.0629
		(-1.02)	*(-0.54)*	*(-0.67)*	*(-0.76)*
INST		0.8849***	0.7793***	0.8047***	0.8327***
		(3.44)	*(3.01)*	*(3.08)*	*(3.21)*
Q4		0.1800	0.2101	0.2041	0.2006
		(1.11)	*(1.29)*	*(1.24)*	*(1.23)*
LOSS		-0.4561**	-0.4127**	-0.4352**	-0.4317**
		(-2.31)	*(-2.13)*	*(-2.24)*	*(-2.20)*
N		33,966	33,966	33,966	33,966
Adj. R^2 (%)		0.19	0.29	0.27	0.25