Tweeting in the Dark: Corporate Communication and Information Diffusion

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Abstract

I investigate the link between firms' voluntary disclosure strategies on social media and their equity returns. I construct a novel and comprehensive database of over 7 million tweets posted by S&P 1500 firms and use text analysis methods to assess the effect of corporate tweets on announcement returns. I find evidence consistent with firms using the timing, tone, and content of tweets strategically. Firms with negative earnings surprises have higher announcement returns when they tweet about financial news, suggesting that firms can use social media to bolster their stock prices during periods of poor performance. This result holds mainly for firms with higher retail investor ownership, consistent with social media being a primary information source for investors with a high cost of information acquisition and processing.

Keywords: Social Media, Strategic Disclosure, Price Formation.

JEL Classification: G01, G14, G30.

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1. Introduction

Social media has changed the way firms communicate with investors by giving them a direct, instantaneous, and network-enhanced communication channel. Firms can now directly transmit information to shareholders through Twitter, Facebook, YouTube, and Instagram among others. In 2013, the SEC announced that companies could use social media to disseminate material information as long as investors were alerted that social media was being used to announce such information. Despite the regulatory attention social media has received, these channels remain voluntary forms of communication. This means that managers have the discretion to disclose or withhold information on social media as they see fit. Given the current regulation, corporate disclosures on social media must be studied in a setting in which firms optimally choose their disclosure strategy and investors anticipate that firms may disclose news strategically.

The incentives of managers are likely to be an important determinant in the information disclosures investors observe on social media. In fact, recent empirical evidence shows that firms are more likely to disclose good news than bad news on their social media platforms (see Jung et al. (2018)). Yet the effects of strategic disclosure and stock prices remains understudied. In light of these facts, this paper provides a novel empirical investigation to address the following research question: what is the link between firms' disclosure strategies on social media and their equity returns?

I exploit firms' discretionary use of social media in disseminating quarterly earnings announcements to examine the relationship between disclosure strategies and equity returns at daily and intradaily frequencies. By focusing on the voluntary disclosure of information on Twitter following mandatory earnings announcement events it is possible to disentangle the impacts of the voluntary disclosure decision from the impacts of the news itself. The SEC requires that firms announce their earnings results at the end of each fiscal quarter. These announcements are actively anticipated by the market and any deviation from the market's expectation ultimately determines the reaction of the stock price to the announcement. By using the deviation from analysts' forecasts, i.e., the actual earnings per share minus the analysts forecast, I am able control for the news itself and isolate the impact of the voluntary disclosure decision on equity returns.

My study focuses on the popular social media site Twitter, which was created in 2006 as a free service that allows users to communicate through short messages of up to 280 characters, known as "Tweets." I focus on Twitter because unlike many other social media platforms, Twitter was designed for sharing news and information in real-time. Also, it has surpassed other social media platforms in terms of general corporate adoption and for disseminating investor-related announcements (see Jung et al. (2018). I construct a novel and comprehensive dataset of tweets by S&P 1500 firms that aggregates over 7 million individual tweets and represents the complete tweeting history of more than $1,000$ firms from January 2014 through December 2018. One of the primary challenges underlying the research design is the detection of financial news disclosure on Twitter. I use text analysis methods to identify tweets related to earnings announcement news and focus on the tweets over the three-day window [–1, +1] around the announcement.

In the empirical part of my study I document three important results. First, I find that tweeting has an asymmetric effect on announcement returns, depending on whether firms tweet about financial news on positive or negative earnings surprise days. In particular, firms with negative earnings announcements have higher announcement returns when they tweet about their earnings news. This result is supported by a separate high-frequency analysis. The speed of information flow on Twitter creates a unique setting in which to study the immediate reaction of investors to tweets about financial news. I find that when firms with negative earnings surprises tweet about financial news, their abnormal cumulative returns appreciate substantially in the 30 minutes following the tweet. Second, I provide evidence that the dissemination of public information on social media matters more for retail investors, which tend to have higher costs of information acquisition and processing. Finally, I employ natural language processing techniques to investigate the strategic use of tone and information content in tweets.

The results I document are consistent with firms using Twitter strategically. In line with previous research, I find that firms are more likely to tweet about their financial results in instances in which they meet or beat analysts' estimates. Next I study the tone of financial news disclosures on

Twitter. Generally, tweets have a positive linguistic tone, independent of whether firms are disclosing financial news around a positive earnings surprise announcement (good news) or a negative surprise earnings announcement (bad news). Finally, I compare the information content of tweets around good news and bad news. Notably, tweets are less likely to mention "earnings per share" and more likely to mention "dividends" on days with negative earnings surprises. Both earnings per share and dividends are closely watched by investors and communicate the financial well-being of a firm. These results suggest that firms not only strategically choose when to tweet about earnings announcements, but also what kind of information to include in their tweets.

I use a model to shed light on the mechanisms through which strategic voluntary disclosure impacts investors' expectations and ultimately the price of firms' equity. I examine the effects of strategic voluntary disclosures made after earnings announcement events using a framework introduced by Goto et al. (2009). The model analyzes disclosures in terms of a verifiable reports framework in order to capture the the broad limits imposed by the accounting system. Even though managers have discretion in whether or not to disclose information on social media, corporate disclosures must be truthful. In this model, a firm has multiple projects, each which can succeed or fail. The firm's manager observes some of these outcomes, while investors observe only the public disclosure made by the manager. The manager is free to disclose some or all of what he knows at an interim date, though they cannot concoct false information. The disclosure policy of the manager is driven by the objective of maximizing the price of the firm. At the same time investors appropriately anticipate the manager's disclosure policy, and price the firm accordingly. This gives rise to a game of incomplete information.

I augment Goto et al.'s (2009) model to include a mandatory disclosure event which occurs at the start of the game. Each firms announces their quarterly earnings results to the market and investors update their prior probability that a dimension of the firm will be successful. If a firm announces earnings below (above) the markets expectations, the expected probability that a business dimension succeeds becomes lower (higher). I interpret the positive (negative) tone of financial news tweets as a disclosure of a success (failure). In particular, I examine two manager strategies: one in which the manager follows a strategic disclosure policy (only disclosing successes), and another in which the manager follows a full disclosure policy. The model shows that firms with a negative earnings surprise have higher expected returns when moving from a full disclosure policy to a strategic disclosure policy. The intuition is that the marginal benefit of strategically disseminating information on social media is higher for firms that are less likely to have good news to disclose. Hence, the model predicts that stock prices will rise more for firms that follow a strategic disclosure policy following a relatively poor earnings announcement.

A key assumption in my theoretical framework is that investors are uncertain about the information endowment of managers. The probability that a manager is informed about the outcome of a business dimension at the interim date of the model captures the relative information uncertainty. This parameter can be thought of as the level of investor sophistication. Hence the more information uncertainty there is the less sophisticated the investors tend to be. The model predicts that the jump in expected returns, when going from a full disclosure policy to a strategic one, is increasing in the relative level of information uncertainty.

Given the short period of time between financial news tweets and mandatory quarterly earnings announcements, often just a few hours, it is reasonable to assume that investors with a high cost of information processing may be uncertain about the information endowment of managers at the time they read a financial news disclosure on Twitter. Inattention may seem unwise, however, if time and attention are costly, such behavior may be completely rational (see, for example Hirshleifer and Teoh (2003)). In general retail investors have a higher cost of information acquisition and processing and therefore the marginal benefit of strategically disseminating information on social media is higher for firms with more retail investor ownership. In line with this prediction, I find that the positive relationship between tweeting after a negative earnings announcement and daily returns is stronger in firms with relatively high retail ownership. Moreover, in a separate analysis looking at investors' demand for information, I find that tweeting about financial news is associated with higher demand for SEC filings. This result further supports the hypothesis that investors who rely on Twitter for information suffer from limited attention biases.

Related literature

This study contributes to three strands of research, of which the first concerns investor attention and asset prices. Previous work has focused primarily on modeling and empirically documenting the effects of investors limited attention. In this literature limited attention is used to help explain pricing phenomena such as predictable price moves (Cohen and Frazzini, 2008), post-earnings announcement drift (DellaVigna and Pollet, 2009), under- and overreactions to news (Hong and Stein, 1999), and return comovements (Peng and Xiong, 2006). In these studies firms do not actively take advantage of investors attention, in contrast my study shows that firms exploit the limited attention of investors to support their price, especially when the firm is performing poorly. Social media gives firms more control over their information environment. In the case of Twitter, the 280-character limit allows firms to select the particular information from an announcement which investors will read first. This is especially important since individuals have the tendency to attend less to information that requires greater cognitive processing, and therefore the short format of tweets can increase the salience of selected information.

This study also contributes to the literature studying how media and stock prices. Huberman and Regev (2001) was one of the first papers to established that the newspaper articles can effect stock returns, even in the absence of new fundamental information. Fang and Peress (2009) and Fedyk (2018) show that the effects of media on asset prices, in the absence of new information, may be driven by the role media plays in alleviating informational frictions. My findings indicate that the results of this literature are also true for new types of media, such Twitter. Furthermore extant research studies media produced by third-parties (Engelberg and Parsons (2011), Tetlock (2007)), by contrast I study firm-initiated media.

Finally, I contribute to a new literature evaluating the role social media plays in financial markets. Bartov et al. (2017) investigate individual investors' use of social media to share information and insights about stocks, and they show that the aggregate opinion from these tweets can predict a firm's forthcoming quarterly earnings and announcement returns. Blankespoor et al. (2014) examine how the use of social media by tech firms is associated with improved market liquidity. They find that the additional dissemination of firm-initiated news via Twitter is associated with lower abnormal bid-ask spreads and greater abnormal trading depths. Bhagwat and Burch (2016) investigate whether Twitter provides firms an effective and strategic way to mitigate investors' limited attention and find that when a firm's earnings surprise is small and positive, the magnitude of announcement returns is higher. Finally, Jung et al. (2018) study whether firms use social media to strategically disseminate financial information and find that firms are less likely to disseminate news via Twitter when the news is bad and when the magnitude of the bad news is worse, consistent with strategic behavior. I complement this literature by studying the effects of strategic discloses through Twitter on asset prices. To the best of my knowledge, this paper provides the first empirical evidence on the strategic information content and tone of tweets across positive and negative earnings surprise days. This paper provides the first high-frequency analysis of returns– by focusing on a short time frame of just 30 minutes before and after each tweet, this analysis helps alleviate the concern that results are driven by something other than the firm's tweeting activity.

The remainder of the paper is organized as follows. Section 2 describes the dataset and section 3 discusses the regulatory setting of disclosures using social media. In section 4 I introduce the theoretical background and empirical implications, and in section 5 I detail the empirical methodology and results. Section 6 presents robustness analyses and section 7 concludes.

2. Institutional Background and Data

A. SEC rules on social media

The SEC has embraced social media and other information technologies in an effort to promote widespread access to corporate information (SEC, 2013). In 2013, the SEC officially stated that social media can be used as a channel for the disclosure of material nonpublic information and provided guidance on the application of Regulation Fair Disclosure (Reg. FD) to social media (SEC, 2013).[1] Nevertheless, social media remains generally unregulated. More specifically, firms are not prohibited from increasing the dissemination of good news and minimizing the dissemination of bad news on social media.

In this paper I investigate the use of social media to disclose earnings announcement news. Because of the careful regulation around earnings announcements, it is likely that firms will only disclose earnings news on social media if this disclosure is accompanied by an official disclosure to the SEC. The SEC requires most listed companies to file a Form 10-Q (quarterly financial report) within 40 days of the end of the quarter.[2]. In the days leading up to the earnings announcement, firms can discuss their preliminary earnings results on social media as long as the firm files a Form 8-K (current report), notifying the SEC and market participants of the impending information disclosure.[3] Due to the importance of information released during earnings announcements, communication of earnings news is carefully regulated. Therefore, it is reasonable to assume that messages on Twitter serve to broaden the dissemination of announcement information or highlight specific aspects of an earnings announcement rather than to reveal new information about the earnings announcement.

Prior studies investigate the information content, timing, and tone of financial statement disclosures (Rogers et al., 2011; Kothari et al., 2009; Davis et al., 2015). This study shows that in addition to the impact of the disclosure itself, the distillation and dissemination of financial disclosures can affect how investors process information.

[1]On July 3, 2012, the CEO of Netflix, Reed Hastings, posted the following message to his personal Facebook page: "Congrats to Ted Sarados, and his amazing content licensing team. Netflix monthly viewing exceeded 1 billion hours for the first time ever in June." The nonpublic information disclosed in the tweet, 1 billion hours, represented a 50% increase in viewing hours from Netflix's January 25, 2012, announcement. Netflix's stock price rose from $70.45 at the time of Hastings's Facebook post to $81.72 at the close of the following trading day. Because material and nonpublic information was exclusively disclosed through Facebook and Netflix had not previously informed shareholders that the CEO's Facebook page would be used to disclose nonpublic information, Hastings's post was found in violation of Reg. FD.

[2]Nonaccelerated filers with a public float of less than $75 million are granted 45 days. Companies typically file this report and their Form 10-K (annual financial report) in the last two days of the required filing period (Amir and Livnat, 2005)

[3]It is common practice for firms to disclose preliminary earnings results. Amir and Livnat (2005) find that 80% of firms in their sample consistently issue preliminary earnings announcements—on average, 26 days after quarter-end.

B. Why Twitter?

The general goal of this paper is to examine the role of social media in the disclosure of corporate information. From a practical point of view, however, there are many reasons to focus on the Twitter platform. Twitter, a micro-blogging network intended for sharing news, content, and information, is the social media platform most widely adopted by S&P 1500 firms (Jung et al., 2018). Twitter connects more than 300 million monthly active users who post, read, and interact with short messages known as "tweets". Unlike many other social media platforms, Twitter has a strong emphasis on real-time information–this enables firms to broadcast financial news directly and instantaneously to a large social network. Increasingly, investor relations departments are using Twitter to reach investors with messages about earnings announcements, management changes, and public relations crises. A growing number of companies are even beginning to create Twitter accounts specifically for investors, for example, Ford Motor Co. (@FordIR), T-Mobile (@TMobileIR), and CVS Health Corp (@CVShealthIR).

Given that investors' information processing capacity is not infinite, there are a number of reasons Twitter may be a primary source of information for some investors. First, standard asset-pricing models typically assume that markets distill new information and incorporate it into their expectations instantaneously–in reality, such distillation and estimation is limited by investors' cost of acquiring and processing information (see Cohen and Frazzini (2008), DellaVigna and Pollet (2009), Hirshleifer and Teoh (2003), Hong and Stein (1999), Peng and Xiong (2006)). The 280-character limit on tweets, the equivalent on average 45 of words, can potentially increase the salience of the information. Salience determines which information will most likely grab people's attention and have the greatest influence on their perception of the world. Second, unlike many other important information channels such as the business press, analysts' reports, and newswire services, Twitter is free, reducing the upfront costs of acquiring corporate information. Finally, Twitter is a push technology, therefore, firms can initiate the information transaction rather than waiting for investors to request the information. Consequently, potential investors who might not otherwise seek out information can have it at their finger tips.

C. *Data collection and sample selection*

To study how disclosure strategies are shaping the link between corporate information dissemination on Twitter and stock returns, I construct a dataset of 7,132,461 individual tweets posted by S&P 1500 firms from January 2014 through December 2017. This firm-tweet data is merged with financial data and market data to relate tweeting activity to announcement returns and short-run continuations in returns.

I begin with an initial sample of 2,454 firms, which includes all historical S&P 1500 index constituents from 2006 (the year Twitter was founded) through 2017. From the starting sample of 2,454 firms, I identify 1,215 firms with active Twitter accounts.[4]

In the Appendix I document that on average larger firms and, incremental to size, firms belonging to the S&P 500 index have a higher probability of having a Twitter account. This result suggests that having a Twitter account is not a substitute for overall visibility but rather a complement to it. Firms with lower book-to-market ratios and firms with relatively higher valuations than their industry peers have a higher probability of having a Twitter account. Technology companies and other companies in industries that have fewer physical assets tend to have low book-to-market ratios and thus are more likely to have Twitter accounts. In addition, firms in more innovative, knowledge-intensive industries also tend to have a higher probability of having a Twitter account. Please refer Appendix Table A1 for details.

After gathering the sample of Twitter usernames, I assemble a complete history of tweets generated by the 1,215 accounts from January 1, 2014, through December 30, 2017, resulting in a sample of 7,132,461 individual tweets. To isolate firm-initiated content that is visible to the firms' followers, I exclude tweets that are reply tweets and retweets.[5] This process reduces the sample to

[4] I started the search on each firm's corporate website. If no Twitter handle was mentioned on the corporate website, I proceeded to search directly on Twitter. The search was conducted in October 2017; therefore the sample is composed of firms which had active Twitter accounts in October 2017.

[5] A reply tweet is a public tweet directed at a specific person. Reply tweets do not appear in the feeds of everyone following the firm; rather, they appear only in the feed of the specific user to whom the firm is replying and in the feed of anyone else who follows both the replying firm and the user receiving the reply. A retweet is the reposting of another Twitter user's tweet on the firm's own profile. Unlike reply tweets, retweets appear in the feed of everyone who is following the firm that reposts the tweet. However, the retweet itself is

3,305,257 individual tweets.

Quarterly earnings announcement dates and analyst consensus forecasts are obtained from Compustat and I/B/E/S, respectively. Daily stock prices are obtained from CRSP, and institutional ownership data are obtained from the Thomson Reuters 13F database. I exclude observations that are lacking necessary data from Compustat, CRSP, I/B/E/S, or Thomson Reuters, yielding a final sample of 1,067 firms and 14,222 firm-quarter observations.

Appendix Table A2 presents the frequency distribution of tweets and firm-quarter observations by calendar quarter. In my sample, the frequency of tweets over time is relatively flat, while the number of firm-quarter observations increases over the sample. This pattern is to be expected, because some Twitter users in the sample were not active at the start of the sample period.

There is considerable heterogeneity across firms' Twitter accounts, which suggests that the effect of tweeting may vary by firm. To address this concern I use firm fixed effects and standard errors clustered by firm. I also control for the number of retweets when measuring the impact of firm tweets. Appendix Table A3 presents descriptive statistics related to tweet characteristics.

In order to study the high-frequency dynamics of stock returns around earnings disclosures on Twitter, I use minute-level price data from Bloomberg. Due to data availability this dataset spans from November 2019 through July 2021. Tweets are matched to the price data using the same procedure as outlined above.

To further investigate fundamental information acquisition, I utilize the SEC's EDGAR log file dataset. This dataset is a collection of web server log files that allows researchers to study firm-specific web traffic of individuals downloading SEC filings. EDGAR is the central repository for all mandatory SEC filings, and the daily-level EDGAR search volume for each firm is a direct measure of investors' fundamental information acquisition. EDGAR log file data are obtained from James Ryans's webpage.[6]

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not original content created by the firm.

[6]The summarized EDGAR log files used in this paper are available for academic use at http://www.jamesryans.com.

D. *Identifying financial news tweets*

One of the primary challenges underlying the research design is the detection of financial news tweets. Following prior research, I use textual analysis to identify these tweets (see, for example, Bartov et al. (2017) and Jung et al. (2018)). I use a classification scheme based on a dictionary of key words and phrases; each tweet is considered earnings news if it contains two or more of the terms found in this dictionary.[7]

Using this textual classification approach, I identify 19,148 tweets (5,549 firm-quarters, 783 unique firms) that contain information directly related to earnings announcements. Examples of financial news tweets in the sample are provided in Appendix Figure 5. As one would expect, financial news tweets are concentrated around earnings announcement periods. The number of financial news tweets in a 10-day window around the announcement represents, on average, approximately one-fourth of all tweets in that period.[8]

Figure 1 depicts the total number of financial news tweets that are posted each hour in the 48 hours before and after earnings are announced. On average, financial news tweets reach their peak numbers the two hours after a quarterly earnings announcement; however, a considerable portion of the distribution of financial news tweets are posted in the days before and after the announcement.

E. *Measuring network impact*

Because Twitter is an interactive network, it is important to consider the network effects at play when measuring the relative impact of individual tweets. When a tweet is posted by a firm, this message is immediately accessible to the firm's followers on their Twitter account. These followers have the option to interact with the tweets; if the tweet is retweeted or liked by one of the firm's followers, then the tweet can be seen by both the firm's followers and the other user's followers. As the process of retweeting and liking continues, a tweet can potentially spread through the entire

[7] The dictionary of key words and phrases can be found in the Appendix.
[8] Summary statistics are provided in Appendix Table A4.

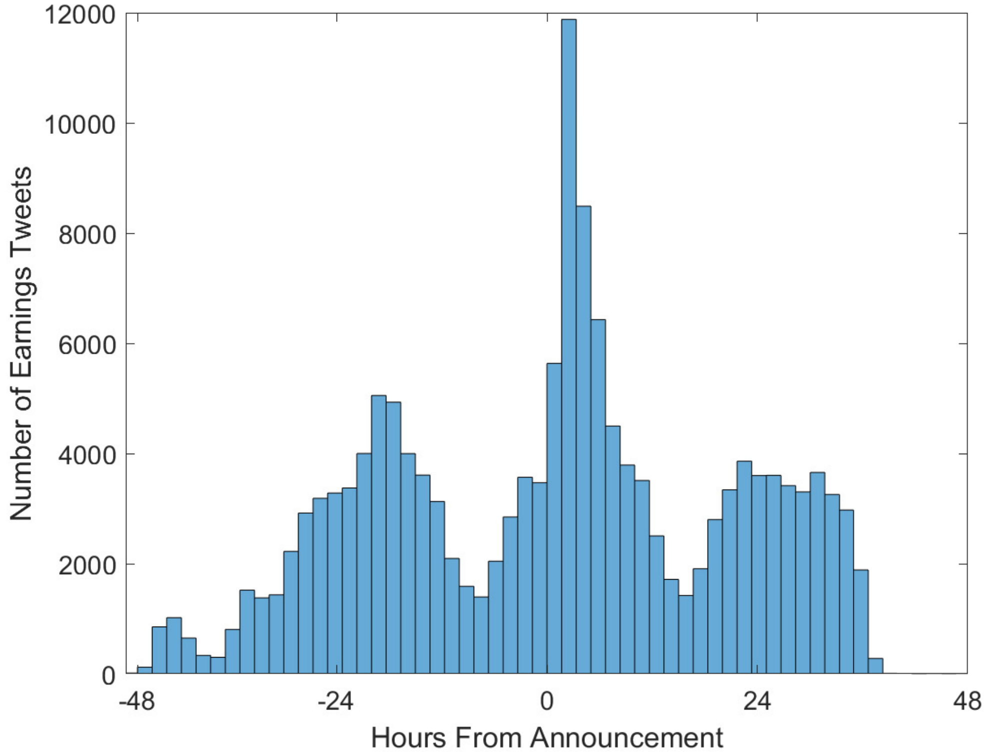


Figure 1: Tweeting around earnings announcements. This figure depicts the relationship between the number of financial news tweets and the number of hours away from firms' earnings announcements. All tweets included in the figure were posted during the sample period (Jan. 2014 through Dec. 2017) by S&P 1500 firms and meet basic minimum word requirements to be considered financial news tweets.

network.

To capture these network effects I measure the impact of firms' financial news tweets (*FinNewsTweetImpact*) in two ways. First, I use the IHS transformation of the number of financial news tweets as a naive proxy for the impact of tweets in the network. Second, I multiply the IHS transformation of the number of financial news tweets by the IHS transformation of the number of financial news retweets to further capture the diffusion of tweets in the network.

3. Theoretical Setting

An extensive theoretical literature has studied when and why limited voluntary disclosure is likely to occur. The "unraveling result" established by Grossman and Hart (1980), Grossman (1981), and Milgrom (1981) identified six conditions under which firms voluntarily disclose all private information in equilibrium. One of the most fragile conditions is that investors must be fully informed about the manager's information endowment. If investors are uncertain whether managers have private information, the managers may withhold information in equilibrium.

Disclosures made through social media channels must be truthful and accurate, as do all other forms of disclosure by regulated firms. However it is left up to the managers' discretion whether or not to disclose information on social media at all. Therefore, a firm's choice to disclose information on social media may reflect the strategic decisions of managers who have a material interest in the reaction of the market to new information. The strategic disclosure model of Shin (2003) formalizes the concept that "although the manager has to tell the truth, he cannot be forced to tell the whole truth" (p. 108). Goto et al. (2009) extend Shin's analysis to investigate the effects of strategic disclosure on the time-series behavior of stock returns in comparison to the effects of full disclosure.

A. Model

I examine the effects of voluntary strategic disclosure after earnings announcement events using the model introduced by Goto et al. (2009). In my setting the success of each firm depends on N independent and identical dimensions, where exante each dimension of the business succeeds with probability r and fails with probability $1 - r$. There are three dates, 0, 1, and 2. At date 0, a firm announces its quarterly earnings results to the market and investors update their prior on r. If a firm announces earnings below (above) market expectations, the probability that a business dimension succeeds becomes $r_l < r$ ($r_h > r$). Each dimension the firm's business is realized by date 1 with probability θ and observed by the firm's manager. At date 1 managers observe s number of successes and f number failures, and have the opportunity to voluntarily disseminate s' successes and f'

failures (where $0 \leq s' < s$ and $0 \leq f' < f$), presumably via social media. It is important to note that the earnings announcement at $t = 0$ is a mandatory disclosure, while the use of social media at $t = 1$ is not required by regulators. By the final date, the outcomes of all business dimensions become common knowledge and the firm is liquidated. The liquidation value of the firm depends on the total number of successes (k) and failures ($N - k$). Each successful business dimension corresponds to a jump up in a binomial pricing tree that increases the liquidation value by a factor of u, and each failed project corresponds to a jump down by a factor of d.

At date 1 there is asymmetric information between managers and investors. The manager observes the successes and failures of each business dimension as they are realized, but investors only observe the disclosure by managers. It is important to point out that managers cannot lie about the success of a project (hence $0 \leq s' < s$), but they are free to disclose successes and withhold disclosure of failures if they deem it favorable. The idea is that a manager's disclosures can be verified at a later date, and therefore an outside party, such as a court, can impose a penalty if a past disclosure is found to be untrue. That said, the amount of private information the manager has at date 1 is not verifiable, and therefore a manager is free to withhold the outcomes of projects if those outcomes are unfavorable.

I examine two manager strategies: one in which the manager follows a strategic disclosure policy (only disclosing successful projects at date 1), and another in which the manager follows a full disclosure policy (disclosing the outcome of all projects realized at or before date 1). I do not consider the strategy of no disclosure since there is always an incentive to deviate at $t = 1$ by disclosing some successes, and hence this strategy is never supported in equilibrium.

Under reasonable parametric assumptions the model shows that the jump in expected returns associated with using a strategic disclosure strategy is decreasing in r. Since investors update their prior on r at date 0, this means that the expected return when using a strategic disclosure strategy is stronger for firms which announce a negative earnings surprise at date 0 than for firms that announce positive earnings surprise (see Appendix section E for details).

4. Empirical Design and Results

A. *Disclosure strategy*

I begin my empirical analysis by investigating the relevant drivers of tweeting about financial news. To test whether firms have a full disclosure policy or whether the disclosure depends on the extent that a firm is revealing positive or negative news, I estimate the following regression:

$$\begin{aligned} FinNewsTweets_{i,t} = \alpha + \beta_1 UnexpectedEarnings_{i,t} \\ + \beta_2 X_{i,t} + \theta_i + \psi_t + \varepsilon_{i,t}. \end{aligned} \tag{1}$$

The control variables, $X_{i,t}$, include $StockMarketIndex_{i_t}$, $Size_{i,t}$, $B/M_{i,t}$, $Analysts_{i,t}$, $Q4_{i,t}$, $Loss_{i,t}$, $InstitutionalOwnership_{i,t}$, $TwitterNetworkSize_i$, and $VerifiedTwitterAccount_i$. To mitigate the influence of outliers, all continuous variables are winsorized at the 1st and 99th percentiles. Appendix Table A4 reports summary statistics on the variables used to estimate equation (1). All variables are defined in detail in Appendix Table A5.

Table 1 displays the coefficient estimates. In columns (1) and (2) I report the results of estimating equation (1) with a probit model. The dependent variable, $FinNewsTweetDummy_{i,t}$, is a binary outcome variable equal to 1 if a firm tweets about earnings over the three-day window [–1, +1] around the earnings announcement and zero otherwise. The variable $SUE_{i,t}$ (standardized unexpected earnings) is the firm's actual earnings minus the analyst consensus forecast of earnings, standardized by the standard deviation of analyst forecasts. This variable captures the "surprise" aspect of the earnings news.

In columns (1) and (2), SUE and $NegativeSurprise$ have significant coefficients at 1%. This indicates that the choice to tweet about financial news does in fact depend on the extent to which a firm is revealing positive or negative news. This result is in line with the finding of Jung et al. (2018) and suggests that on average firms tend to strategically disclose news on social media.

The probit specification in Table 1 enables me to compare characteristics across firms that impact the likelihood of tweeting about financial news. I note several interesting patterns. Firms that belong to the S&P 500 index (large-cap)–that is, large, well-known firms—are more likely to tweet about financial news. It is important to note that this result holds despite controlling for the size of firms. Firms with lower book-to-market values are also more likely to tweet about financial news. On average, technology companies and other companies in industries that do not have a lot of physical assets tend to have low book-to-market ratios.

One concern about using a probit model is that fixed effects cannot be controlled for. Therefore I re-estimate equation (1) using an OLS model with firm and quarter fixed effects. In columns (3) and (4) I report the results of estimating equation (1) with an OLS model. The dependent variable, $FinNewsTweetCount_{i,t}$, is the number of financial news tweets over the three-day window [–1, +1] around the earnings announcement. All other variables remain the same.

In columns (3) and (4) of Table 1 both SUE and $NegativeSurprise$ have significant coefficients. These results are consistent with those of the probit specification and reaffirm that the choice to tweet about financial news depends on the extent to which a firm is revealing positive or negative news. *Loss* changes sign when I control for firm and quarter fixed effects–this indicates that a firm is less likely to tweet about financial news when its net income is negative than when its net income is positive.

B. Tweeting and announcement returns

My primary research question focuses on whether there is a link between corporate information dissemination on social media and stock returns. To answer this question I investigate the relationship between announcement returns and financial news tweets. If managers follow a strategic disclosure scheme in equilibrium, then on average one would expect to see negative earnings surprise to be met with a larger increase in returns if managers strategically tweet about financial news. To test this

Table 1: When Firms Tweet about Financial News

In this table I test whether firms have a full disclosure policy or whether their disclosure depends on the extent to which they are revealing positive or negative news. In columns (1) and (2) I estimate equation (1) with a probit model, and the dependent variable is $FinNewsTweetDummy_{i,t}$, a binary outcome variable equal to 1 if a firm tweets about earnings over the three-day window [-1, +1] around the earnings announcement and zero otherwise. In columns (3) and (4) I estimate equation (1) using an OLS model with firm and quarter fixed effects, and the dependent variable is $FinNewsTweetCount_{i,t}$, the number of financial news tweets over the three-day window [–1, +1] around the earnings announcement. To mitigate the influence of outliers, all continuous variables are winsorized at the 1st and 99th percentiles. See Appendix Table A5 for variable definitions. Standard errors are clustered at the firm level and reported in parentheses beneath the coefficient estimates. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Probit		**Fixed Effects**	
	Fin News Tweet Dummy		*Fin News Tweet Count*	
	(1)	(2)	(3)	(4)
Std. Unexpected Earnings	0.017***		0.007***	
	(0.005)		(0.003)	
Negative Surprise		-0.096***		-0.037*
		(0.034)		(0.021)
Additional Tweet Count	0.004***	0.004***	0.008***	0.008***
	(0.002)	(0.002)	(0.003)	(0.003)
SP500	0.330***	0.330***	-0.059	-0.055
	(0.107)	(0.107)	(0.237)	(0.238)
SP600	-0.207**	-0.209**	-0.012	-0.013
	(0.085)	(0.085)	(0.073)	(0.074)
Size	0.178***	0.177***	-0.012	-0.010
	(0.031)	(0.031)	(0.099)	(0.099)
BM	-0.288***	-0.288***	-0.156	-0.156
	(0.110)	(0.110)	(0.266)	(0.266)
Loss	0.216***	0.210***	-0.124**	-0.127***
	(0.069)	(0.069)	(0.048)	(0.049)
Q4	-0.030	-0.032	-0.029	-0.031
	(0.025)	(0.025)	(0.025)	(0.025)
Analysts	0.005	0.004	-0.005	-0.005
	(0.005)	(0.005)	(0.003)	(0.003)
Institutional Ownership	-0.098	-0.091	0.173	0.170
	(0.167)	(0.168)	(0.288)	(0.288)
Twitter Network Size	-0.209***	-0.210***		
	(0.025)	(0.025)		
Verified Twitter Account	-0.017	-0.014		
	(0.099)	(0.099)		
Firm FE	No	No	Yes	Yes
Quarter-Year FE	No	No	Yes	Yes
Adjusted (Pseudo) R^2	(0.098)	(0.097)	0.624	0.624
Observations	14,045	14,045	14,222	14,222

hypothesis I estimate the following model:

$$\begin{aligned} CAR_{i,t} &= \alpha + \beta_1 NegativeSurprise_{i,t} + \beta_2 FinNewsTweetImpact_{i,t} \\ &+ \beta_3 NegativeSurprise_{i,t} \times FinNewsTweetImpact_{i,t} \\ &+ \beta_4 X_{i,t} + \theta_i + \psi_t + \varepsilon_{i,t}. \end{aligned} \tag{2}$$

In equation (2), the dependent variable, $CAR_{i,t}$, is the Carhart (1997) cumulative abnormal return for firm i over the three-day window [–1, +1] around the quarterly earnings announcement. $NegativeSurprise_{i,t}$ is an indicator variable equal to one if firm i misses its analyst consensus forecast in quarter t, and zero otherwise. $FinNewsTweetImpact_{i,t}$ captures the extent to which a firm i tweets about their quarterly earnings announcement over the three-day window [–1, +1] around the announcement. First, I use the inverse hyperbolic sine (IHS) transformation of the number of financial news tweets. Second, I multiply the IHS transformation of the number of financial news tweets by the IHS transformation of the number of financial news retweets to capture diffusion of information in the network. $NegativeSurprise_{i,t} \times FinNewsTweetImpact_{i,t}$ is an interaction term; this variable helps capture the impact of a firm's financial news tweets, given that the firm misses its consensus forecast.

Beating analysts' forecasts of earnings is a concept well studied by researchers. The literature has shown that the market response to earnings surprises is asymmetric. Skinner and Sloan (2002) find that the price reaction to a negative surprise tends to be larger in magnitude than the price reaction to a positive surprise. Moreover, there is a large jump in density when going from firms with a negative surprise of 1 cent to those having no surprise at all, which highlights the high cost of missing analysts' expectations (Matsumoto, 2002).

Furthermore, the premium from having no surprise or a positive surprise even exists in the cases in which the forecasted earnings target is likely to have been achieved through earnings or expectations management Bartov et al. (2002). Given the asymmetry in the market response to positive and negative earnings announcements, I choose to interact $FinNewsTweetImpact_{i,t}$ with the dummy variable $NegativeSurprise_{i,t}$, rather than with the continuous variable $SUE_{i,t}$.

The control variables, $X_{i,t}$, include $Size_{i,t}$, $B/M_{i,t}$, $Analysts_{i,t}$, $SUE_{i,t}$, $Q4_{i,t}$, $Loss_{i,t}$, and $AdditionalTweetImpact_{i,t}$. To mitigate the influence of outliers, all continuous variables are winsorized at the 1st and 99th percentiles. Appendix Table A4 reports summary statistics on the variables used to estimate equation (2). All variables are defined in detail in Appendix Table A5.

In Table 2, equation (2) is estimated using firm and quarter-year fixed effects. For firms that miss their analyst consensus forecast, the effect of tweeting about earnings in column (2) is 0.866 (0.100 + 0.766), which the F-test shows is significant at 1%. The coefficient estimate for *FinNewsTweetImpact* in column (2) is 0.100 and is statistically insignificant, meaning that for firms that meet or beat their analyst consensus forecast, tweeting about earnings is not associated with a change in the announcement return.

The within-group estimates suggest that when the same firm tweets about earnings over different quarters, tweeting has an asymmetric effect on announcement returns depending on whether the firm has a positive or negative earnings surprise. Firms with negative surprises have higher announcement returns when they tweet about earnings news. These results are robust to the measurement of *FinNewsTweetImpact* in columns (3) and (4).

One implication of strategic disclosure is that the jump in expected returns associated with using a strategic disclosure strategy is stronger for firms which announce a negative earnings surprise at date 0. In line with this prediction, I find firms that tweet about financial news following a negative earnings surprise have higher abnormal returns. These results establish a link between corporate information dissemination on social media and stock returns and support the theoretical predictions outlined in section 3.

Institutional ownership

Investors have heterogeneous costs of information acquisition and processing. Unsophisticated investors tend to have higher costs, and thus unsophisticated investors who rely on social media

Table 2: Tweeting and Announcement Returns

This table shows the relationship between cumulative abnormal returns and firms' tweeting behaviors. In columns (1) and (2) *FinNewsTweetImpact* is measured as as *FinNewsTweets* and in columns (3) and (4) as *FinNewsTweets*Retweets*. To mitigate the influence of outliers, all continuous variables are winsorized at the 1st and 99th percentiles. See Appendix A for variable definitions. Standard errors are clustered at the firm level and reported in parentheses beneath the coefficient estimates. *, **, and *** indicates significance at the 10%, 5%, and 1% levels, respectively.

	$CAR_{-1,+1}$			
	(1)	(2)	(3)	(4)
Negative Surprise	-3.447***	-3.762***	-3.447***	-3.648***
	(0.189)	(0.215)	(0.189)	(0.201)
Fin News Tweet Impact	0.280*	0.100	0.071	-0.010
	(0.145)	(0.153)	(0.073)	(0.075)
Negative Surprise × *Fin News Tweet Impact*		0.766***		0.468***
		(0.229)		(0.106)
SUE	0.465***	0.465***	0.465***	0.464***
	(0.028)	(0.028)	(0.028)	(0.028)
Additional Tweet Impact	0.040	0.041	0.047	0.051
	(0.081)	(0.081)	(0.081)	(0.034)
Residual ESV (Ryans)	-0.444	-0.443	-0.444	-0.450
	(0.287)	(0.288)	(0.287)	(0.288)
Size	-2.473***	-2.469***	-2.477***	-2.477***
	(0.409)	(0.410)	(0.410)	(0.411)
Loss	-1.661***	-1.644***	-1.672***	-1.644***
	(0.304)	(0.304)	(0.304)	(0.304)
BM	7.065***	7.067***	7.045***	7.056***
	(0.750)	(0.748)	(0.747)	(0.746)
Q4	0.311	0.299	0.308	0.296
	(0.203)	(0.203)	(0.204)	(0.203)
Firm FE	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes
F-test statistic: $\beta 2 + \beta 3 = 0$		14.054		15.292
F-test p-value		0.000		0.000
No. of firms	1067	1067	1067	1067
Adjusted R^2	0.155	0.156	0.155	0.156
Observations	14,222	14,222	14,222	14,222

may be unaware when a manager has failed to disclose information on social media. As a result, the evidence of predictability should be stronger or even exclusively concentrated among stocks with high retail ownership. To test this hypothesis, I examine the effects of ownership on announcement return predictability.

I identify the percentage of each firm owned by institutional investors using 13F data from Thomson Reuters. As a proxy for retail ownership I use 100% minus the percentage of shares outstanding owned by institutional investors. Based on the average percentage of institutional ownership, I sort firms into high or low retail ownership categories and re-estimate equation (2) on the two subsamples of firms. On average, in the high-retail category firms, institutional investors own 72% of shares outstanding, while in the low-retail category firms, institutional investors own 94% of shares outstanding.

Table 3 reports the regression estimates for both the low- and high-retail ownership subsamples. The estimation results reveal that only firms with high retail ownership and negative surprises experience higher announcement returns if they tweet about earnings news. In particular, the coefficient estimates of *NegativeSurprise*FinNewsTweetImpact* for the high retail ownership firms in columns (3) and (4) are positive and statistically significant at 5% and 1%. In contrast, the coefficient estimates for the low retail ownership firms in columns (1) and (2) are, respectively marginally significant at 10% and statistically insignificant.

Network size

Next, I investigate the relation of the size of a firm's network to announcement return predictability. If tweets are in fact influencing abnormal stock returns, the evidence of predictability should be stronger among firms with larger networks on Twitter. Based on the size of each firm's network of followers, I sort firms into small or large network categories and re-estimate equation (2).

in Table 4 I present regression estimates for both network-size subsamples. The estimation results reveal that only firms with large networks on Twitter and negative surprises tend to have

Table 3: Institutional Ownership: Tweeting and Announcement Returns

This table shows the relationship between cumulative abnormal returns and firms' tweeting behaviors. The sample is split into high and low institutional ownership firms (above or below the sample median of total institutional ownership as a percentage of shares outstanding). In columns (1) and (3) *FinNewsTweetImpact* is measured as as *FinNewsTweets* and in columns (2) and (4) as *FinNewsTweets*Retweets*. To mitigate the influence of outliers, all continuous variables are winsorized at the 1st and 99th percentiles. See Appendix A for variable definitions. Standard errors are clustered at the firm level and reported in parentheses beneath the coefficient estimates. *, **, and *** indicates significance at the 10%, 5%, and 1% levels, respectively.

	Low-Retail Firms		*High-Retail Firms*	
	(1)	(2)	(3)	(4)
Negative Surprise	-4.260***	-4.118***	-3.258***	-3.156***
	(0.299)	(0.276)	(0.318)	(0.298)
Fin News Tweet Impact	0.237	0.097	0.018	-0.026
	(0.258)	(0.167)	(0.185)	(0.084)
Negative Surprise × *Fin News Tweet Impact*	0.646*	0.305	0.732**	0.437***
	(0.385)	(0.243)	(0.293)	(0.121)
Additional Tweet Impact	0.184	0.033	-0.098	0.054
	(0.125)	(0.055)	(0.105)	(0.042)
Residual ESV (Ryans)	0.138	0.142	-1.203***	-1.220***
	(0.405)	(0.405)	(0.426)	(0.426)
SUE	0.474***	0.474***	0.443***	0.444***
	(0.036)	(0.036)	(0.043)	(0.043)
Size	-3.257***	-3.285***	-1.121*	-1.150*
	(0.531)	(0.527)	(0.666)	(0.666)
Loss	-1.638***	-1.657***	-1.486***	-1.458***
	(0.391)	(0.392)	(0.478)	(0.480)
BM	6.034***	6.076***	9.282***	9.235***
	(0.902)	(0.901)	(1.217)	(1.219)
Q4	0.313	0.302	0.316	0.316
	(0.321)	(0.322)	(0.241)	(0.240)
Firm FE	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes
F-test statistic: $\beta 2 + \beta 3 = 0$	6.807	2.917	5.437	9.102
F-test p-value	0.009	0.088	0.020	0.003
No. of firms	529	529	508	508
Adjusted R^2	0.165	0.165	0.151	0.151
Observations	6,948	6,948	6,991	6,991

higher announcement returns when they tweet about earnings news. In particular, the coefficient estimates of *NegativeSurprise*FinNewsTweetImpact* for the large network firms in columns (3) and (4) are statistically significant at 1%. In contrast, the same coefficient estimates for the small network firms in columns (1) and (2) are statistically insignificant.

Table 4: Social Network Size: Tweeting and Announcement Returns

This table shows the relationship between cumulative abnormal returns and firms' tweeting behaviors. The sample is split into large and small network firms (above or below the sample median of Twitter followers). In columns (1) and (3) *FinNewsTweetImpact* is measured as as *FinNewsTweets* and in columns (2) and (4) as *FinNewsTweets*Retweets*. To mitigate the influence of outliers, all continuous variables are winsorized at the 1st and 99th percentiles. See Appendix A for variable definitions. Standard errors are clustered at the firm level and reported in parentheses beneath the coefficient estimates. *, **, and *** indicates significance at the 10%, 5%, and 1% levels, respectively.

	Small-Network Firms		*Large-Network Firms*	
	(1)	(2)	(3)	(4)
Negative Surprise	-3.809***	-3.682***	-3.739***	-3.666***
	(0.313)	(0.289)	(0.303)	(0.288)
Fin News Tweet Impact	0.332	0.141	-0.106	-0.058
	(0.254)	(0.192)	(0.187)	(0.081)
Negative Surprise × *Fin News Tweet Impact*	0.396	0.153	1.039***	0.551***
	(0.385)	(0.387)	(0.273)	(0.114)
Additional Tweet Impact	-0.008	-0.097	0.114	0.082**
	(0.115)	(0.071)	(0.117)	(0.038)
SUE	0.415***	0.413***	0.521***	0.522***
	(0.039)	(0.039)	(0.038)	(0.039)
Size	-2.480***	-2.458***	-2.442***	-2.463***
	(0.631)	(0.626)	(0.524)	(0.522)
Loss	-1.974***	-2.000***	-1.315***	-1.298***
	(0.460)	(0.462)	(0.379)	(0.378)
BM	7.485***	7.446***	6.608***	6.633***
	(1.002)	(0.991)	(1.145)	(1.143)
Q4	0.101	0.087	0.488*	0.485*
	(0.305)	(0.307)	(0.282)	(0.283)
Firm FE	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes
F-test statistic: $\beta 2 + \beta 3 = 0$	3.446	0.633	13.256	15.429
F-test p-value	0.064	0.426	0.000	0.000
No. of firms	621	621	431	431
Adjusted R^2	0.154	0.153	0.158	0.159
Observations	7,025	7,025	7,019	7,019

C. Tweeting and announcement returns: A high-frequency analysis

Twitter was made to share news, content, and information in real time. This platform enables firms to share financial news with their social network, and individuals to have instantaneous access to that information. The speed of information flow on Twitter creates a unique setting in which to study the possible reactions of investors to tweets about financial news. In this section I study the high-frequency dynamics of stock returns around financial news disclosures on Twitter.

My novel dataset of financial news tweets enables me to measure the exact time of information disclosures on Twitter. For each tweet in the dataset, I compile the minute-level return data in the 60-minute window around the tweet and estimate the following model at the minute level:

$$Y_t = (\alpha_{pre} + \alpha_{t>t^*}) + (\beta_{pre} + \beta_{t>t^*})t + (\gamma_{pre} + \gamma_{t>t*})t^2 + \varepsilon_t. \tag{3}$$

In equation (3), t^* is the time of a financial news tweet. The dependent variable Y_t is either the average abnormal cumulative return obtained from buying equities 30 minutes before a tweet and holding them for 60 minutes, or the average minute-level trading volume. The model is a quadratic function of time that includes dummy variables to account for post-announcement jumps in intercept and slope. I test the null assumption that there is no difference in the post-announcement window, $H_0 : \alpha_{t>t^*} = \beta_{t>t^*} = \gamma_{t>t*}$. If the null hypothesis is rejected, two separate functions are fit, one before t^* and one after. The results are aggregate across firms and quarters. Quarters are divided into two groups, positive and negative earnings surprise quarters, according to the standard definition based on analyst consensus forecasts.

Equity Returns

Figure 2 depicts the results visually. In the upper panel of Figure 2 I consider all tweets about financial news within a three-day window around earnings announcement events, in quarters in which earnings are reported above the analyst consensus forecast. The figure depicts the average cumulative return in excess of the same average measured in a control sample, defined using the same time of day in a matched quarter in which tweets do not occur. The matching procedure controls for the level of surprise, relative to the analyst consensus forecast, and the time of day. This strategy allows me to control for the common trend, which is generally upward sloping on days with a positive surprise and downward sloping on days with a negative surprise.

For positive-surprise events (panel (a)), abnormal cumulative returns tend to increase before the tweet and then decline slightly upon the announcement. Turning our attention to negative-surprise events (panel (b)), abnormal cumulative returns tend to appreciate before the tweet and then further appreciate upon the announcement. This observation suggests that the release of financial news on Twitter may help equities during periods surrounding poor earnings announcements.

These results confirm the previous analysis using minute-level data rather than daily data. In Table 5 you can the coefficient estimates based on equation (3).

Trading Volume

Figure 3 shows the high-frequency results for trading volumes. In panel (a) I consider all tweets about financial news within a three-day window around earnings announcement events, in quarters in which earnings are reported *above* the analyst consensus forecast. Instead, in panel (b) I consider quarters in which earnings are reported *below* the analyst consensus forecast.

For positive-surprise events (panel (a)), trading volumes tend to slightly decrease before the tweet and then increase for about 20 minutes immediately after the announcement. For negative-surprise events (panel (b)), trading volumes tend to slightly increase before the tweet and then continue to increase for about 15 minutes immediately after the announcement. This observation suggests that investors do in fact trade on the information released via Twitter. In both panels the concave shape of the function in the 30 minutes following the tweets suggests that trading responds quickly to tweets about financial news but the tweets have only a transitory effect.

Table 5: High Frequency Returns: Regression Analysis

This table shows the coefficient estimates based on the estimation of equation (3). The sample is split into positive and negative news surprise disclosures. In columns (1) and (2) the dependent variable is the cumulative abnormal return obtained from buying equities 30 minutes before a tweet and holding them for 60 minutes. In columns (3) and (4) the dependent variable is the minute-level trading volume from 30 minutes before a tweet to 30 minutes after. Standard errors are reported in parentheses beneath the coefficient estimates. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Abnormal Cumulative Return		Trading Volume	
	Pos. Surp.	Neg. Surp.	Pos. Surp.	Neg. Surp.
Post	1.6070***	0.6947***	-51243.4980***	-26736.1007**
	(0.196)	(0.180)	(16205.046)	(10918.360)
t	0.0270***	-0.0554***	-447.2025	194.7015*
	(0.003)	(0.007)	(457.736)	(102.216)
Post $\times$ t	-0.0731***	0.0138	2613.6193***	1141.6288**
	(0.009)	(0.010)	(832.772)	(493.152)
t^2	-0.0003***	0.0018***	10.2321	-2.6874
	(0.000)	(0.000)	(11.715)	(3.237)
Post $\times$ t^2	0.0007***	-0.0012***	-31.9605**	-10.7904*
	(0.000)	(0.000)	(13.808)	(6.066)
Constant	-0.0679***	0.2137***	21071.2402***	9364.6844***
	(0.022)	(0.055)	(3891.076)	(639.326)
R^2	0.930	0.950	0.501	0.511
Observations	62	62	62	62

D. Tweeting and fundamental information acquisition

Does tweeting encourage fundamental information acquisition? To test this question I use a novel dataset that tracks all web traffic on the SEC's EDGAR servers. The SEC has assembled a log file which records each user request to acquire a specific filing from EDGAR. This dataset allows me to analyze investor acquisition of specific financial disclosures and study the relationship between information acquisition and a firm's tweeting behavior by estimating the following regression:

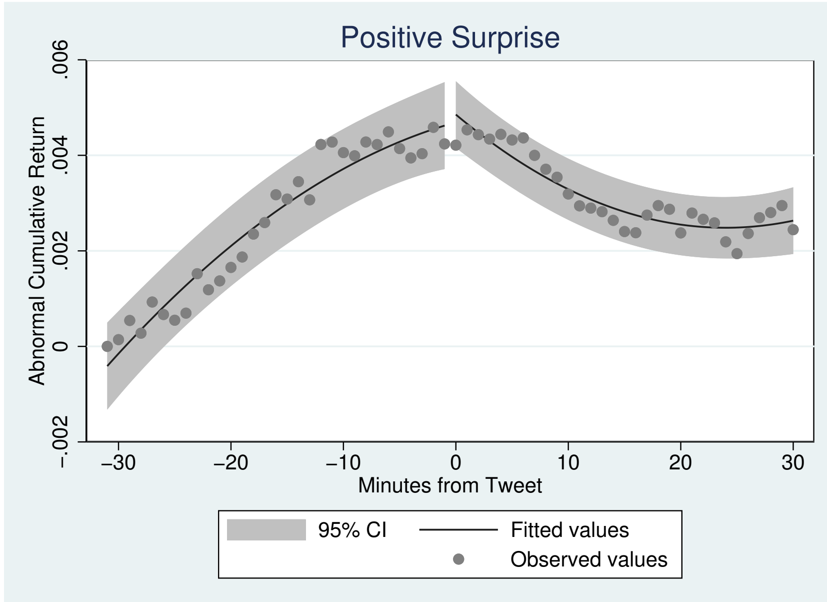
$$\begin{aligned} ESV_{i,t} = \alpha + \beta_1 FinNewsTweetImpact_{i,t} + \beta_2 NegaticeSurprise_{i,t} \\ + \beta_3 X_{i,t} + \theta_i + \psi_t + \varepsilon_{i,t}. \end{aligned} \tag{4}$$

In equation (4), the dependent variable, $ESV_{i,t}$, is the daily EDGAR Search Volume from the

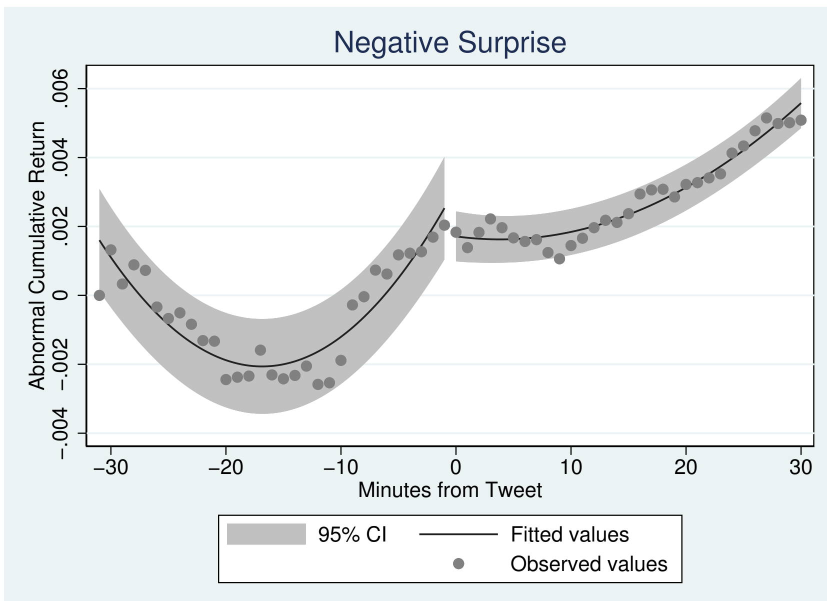
SEC's web server log file data for firm i over the three-day window [–1, +1] around the quarterly earnings announcement. Since the log files must be filtered to remove downloads by computer programs, I use two methods for counting human views in the EDGAR log files developed by Ryans (2017) and Loughran and McDonald (2017). $FinNewsTweetImpact_{i,t}$ captures the extent to which firm i tweets about its earnings announcement over the three-day window [–1, +1] around the earnings announcement.

The control variables, $X_{i,t}$, include $Size_{i,t}$, $B/M_{i,t}$, $Analysts_{i,t}$, $SUEi,t$, $Q4_{i,t}$, $Loss_{i,t}$, and $AdditionalTweetImpact_{i,t}$. To mitigate the influence of outliers, all continuous variables are winsorized at the 1st and 99th percentiles. Appendix Table A4 reports summary statistics on the variables used to estimate equation (2). All variables are defined in detail in Appendix Table A5.

In Table 6, equation (4) is estimated using firm and quarter-year fixed effects. The coefficient estimates for *FinNewsTweetImpact* are statistically significant at the 5% level or higher in all columns except (3), indicating that in most specifications tweeting about financial news is associated with more fundamental information acquisition by individual investors. In columns (2) and (4) I include the interaction term $NegativeSurprise \times FinNewsTweetImpact_{i,t}$; this specification reveals that only firms' tweeting about a positive earnings surprises is associated with higher EDGAR search volumes. Instead, firms' tweeting about negative earnings surprises is not associated with a change in EDGAR search volumes.

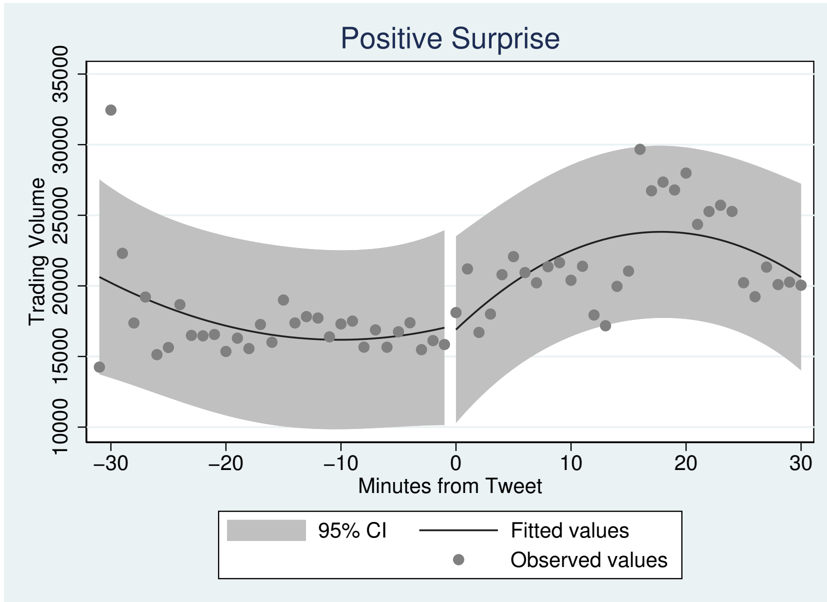


(a)

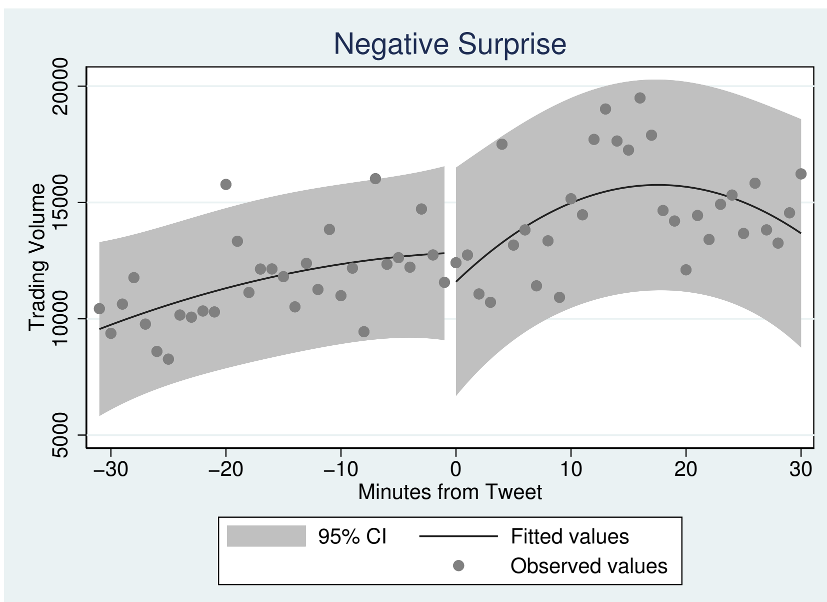


(b)

Figure 2: High frequency equity returns: This figure depicts the average abnormal cumulative return obtained from buying equities 30 minutes before a tweet and holding them for 60 minutes. The abnormal cumulative return is defined as the average cumulative return in excess of the control sample, where the control sample is defined using a matched firm-time where tweets do not occur. The matching procedure controls for the level of surprise, relative the analyst consensus forecast, and the time of day. The sample is split into positive news and negative news disclosures, panel a (panel b) depicts returns around positive (negative) news. The solid lines and shaded areas are based on the estimation of equation (3) where $t^* = 0$ is the time of an earnings related tweet. The null assumption that there is no difference in the post-announcement window, $H_0 : \alpha_{t>t^*} = \beta_{t>t^*} = \gamma_{t>t*}$, and if the null hypothesis is not rejected a continuous quadratic function if fit. Standard errors are estimated at 95%. Returns are in raw log units.



(a)



(b)

Figure 3: High frequency trading volumes: This figure depicts the average trading volume from 30 minutes before a tweet to 30 minutes after a tweet. The sample is split into positive news and negative news disclosures, panel a (panel b) depicts the trading volume around positive (negative) news. The solid lines and shaded areas are based on the estimation of equation (3) where $t^* = 0$ is the time of an earnings related tweet. The null assumption that there is no difference in the post-announcement window, $H_0 : \alpha_{t>t^*} = \beta_{t>t^*} = \gamma_{t>t*}$, and if the null hypothesis is not rejected a continuous quadratic function if fit. Standard errors are estimated at 95%.

Table 6: Tweeting and Fundamental Information Acquisition

This table shows the relationship between the dependent variable, EDGAR search volume, and firms' tweeting behavior. The dependent variable, ESV, is the daily EDGAR Search Volume from the SEC's web server log file over the three-day window [-1, +1] around the quarterly earnings announcement. In columns (1) and (2) I follow log file cleaning procedure developed by Loughran and McDonald (2017), and in columns (3) and (4) I follow Ryans (2017). $FinNewsTweetImpact$ is the IHS transformation financial news tweets in the three-day window [-1, +1] around the earnings announcement. To mitigate the influence of outliers, all continuous variables are winsorized at the 1st and 99th percentiles. See Appendix table A5 for variable definitions. The regression is estimated using OLS with robust standard errors. Standard errors are provided in parentheses beneath the coefficient estimates. *, **, and *** indicates significance at the 10%, 5%, and 1%, respectively.

	Edgar Search Volume			
	(1)	(2)	(3)	(4)
Fin News Tweet Impact	0.025**	0.030***	0.015	0.022**
	(0.011)	(0.011)	(0.010)	(0.011)
Negative Surprise	0.035***	0.044***	0.028***	0.039***
	(0.010)	(0.011)	(0.008)	(0.010)
*Neg Surp*Fin News Tweet Impact*		-0.021*		-0.027**
		(0.012)		(0.011)
Additional Tweet Impact	-0.008	-0.008	-0.013**	-0.013**
	(0.006)	(0.006)	(0.006)	(0.006)
Size	0.261***	0.260***	0.271***	0.270***
	(0.035)	(0.035)	(0.031)	(0.031)
Loss	0.052***	0.051***	0.037**	0.036**
	(0.017)	(0.017)	(0.015)	(0.015)
BM	-0.009	-0.009	-0.021	-0.022
	(0.038)	(0.039)	(0.037)	(0.037)
Q4	0.044***	0.045***	0.020	0.020
	(0.015)	(0.015)	(0.013)	(0.013)
Analysts	0.003***	0.003***	0.002***	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)
Firm FE	Yes	Yes	Yes	Yes
Quarter-year FE	Yes	Yes	Yes	Yes
F-test statistic: $\beta2 + \beta3 = 0$		0.506		0.192
F-test p-value		0.477		0.661
No. of firms	1,030	1,030	1,030	1,030
Adjusted R^2	0.810	0.810	0.809	0.809
Observations	12,484	12,484	12,484	12,484

E. *Tweeting and the speed of information diffusion*

Can firm-initiated tweets increase the speed of information diffusion? Momentum in returns has been explained theoretically and empirically by gradual diffusion of information (Hong and Stein (1999), Hong et al. (2000)). Momentum in stock returns is a longstanding empirical fact; that is, securities which have performed well over the prior 6-12 months continue to outperform relative to those that did poorly, for the next 3-12 months Jegadeesh and Titman (1993).

If tweeting about earnings news increases the speed of information diffusion to the market, then momentum in returns should decrease. To test this prediction I estimate the following regression:

$$Momentum_i = \alpha + \beta_1 EarningsTweetQuarters_i + \beta_2 X_i + \varepsilon_i. \tag{3}$$

In equation (3), the dependent variable, $Momentum_i$, is a proxy for momentum as it is defined in the empirical asset pricing literature (cf. Jegadeesh and Titman (1993)). $Momentum_i$ is measured as the correlation between the series $ExRet_{i,t}$ and the lagged series $ExRet_{i[t-12,t-2]}$, where $ExRet_{i,t}$ is the monthly excess return of firm i. $EarningsTweetQuarters_i$ is the proportion of quarters in which a firm tweets about earnings news over the sample period, January 2014 through December 2017. I construct $Momentum_i$ using $t \in$ {January 2014,..., December 2017} to match the sample period.

The controls, X_i, include $Size_i$, B/M_i, and $Analysts_i$ and are measured using the average value over the sample period. Appendix Table A4 presents the descriptive statistics for the variables used to estimate equation (3). All variables are defined in detail in Appendix Table A5.

In Table 7 *Momentum* is calculated using excess returns relative to 90-day T-bills (columns (1) and (2)) and using Fama-French three-factor excess returns (columns (2) and (4)). In columns (1) and (2) the coefficients are estimated using the full sample of firms, and the coefficient estimates for *FinNewsTweetQuarters* are not statistically significant. However, once the sample is restricted to verified accounts only, in columns (3) and (4), coefficient estimates for *FinNewsTweetQuarters* are −0.041 and −0.040 and are statistically significant at the 1% and 5% levels, respectively. This negative relationship suggests firms with verified accounts that tweet about earnings news more consistently have less momentum in returns. This result suggests firms may be able to increase the speed of information diffusion to investors by tweeting about earnings news. This result is consistent with media's role to disseminate information quickly.

Table 7: Tweeting and the speed of information diffusion

This table shows the cross-sectional relationship between momentum in monthly stock returns and the consistency of tweeting about earnings news. The dependent variable is *Momentum*; in columns (1) and (3) is calculated using excess returns relative to 90 day T-bills and in columns (2) and (4) using Fama-French three factor excess returns. Columns (3) and (4) are estimated using the subsample of firms with verified Twitter accounts. To mitigate the influence of outliers, all continuous variables are winsorized at the 1st and 99th percentiles. See Appendix table A5 for variable definitions. The regression is estimated using OLS with robust standard errors. Standard errors are provided in parentheses beneath the coefficient estimates. *, **, and *** indicates significance at the 10%, 5%, and 1%, respectively.

	All Firms		*Verified Twitter Firms*	
	(1)	(2)	(3)	(4)
Fin News Tweet Quarters	-0.018	-0.002	-0.041***	-0.040**
	(0.011)	(0.013)	(0.016)	(0.020)
BM	0.022	-0.007	0.038*	0.032
	(0.015)	(0.034)	(0.020)	(0.041)
Analysts	0.001	-0.001	0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Size	0.000	0.004	0.004	0.007
	(0.004)	(0.005)	(0.005)	(0.008)
Institutional Ownership	0.010	0.014	0.013	0.003
	(0.032)	(0.036)	(0.049)	(0.066)
Twitter Followers	0.000	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-0.090*	-0.120**	-0.176**	-0.190**
	(0.053)	(0.050)	(0.073)	(0.094)
R^2	0.054	0.022	0.064	0.047
Observations	1,064	848	443	356

F. *Content analysis of tweets*

My analysis confirms that financial news shared on Twitter has a significant impact on the market value of equities in some situations. Specifically, I find that firms with negative earnings surprises tend to have higher daily announcement returns when they tweet about their earnings announcement.

The equity returns patterns that I document are consistent with the model in section 3. These results may also be consistent with models featuring hidden information and adverse selection. To distinguish among these possible models, I provide data from a formal comparison of tweets across positive and negative earnings surprise days.

Table 8 shows the results from a feature extraction exercise. In columns (4)–(6) I consider all tweets about financial news in a three-day window around earnings announcement events. In columns (1)–(3) I consider the remaining tweets, those unrelated to financial news, in the same three-day window. The results are aggregate across firms and quarters. Quarters are divided into two groups, positive and negative earnings surprise quarters relative to the analyst consensus forecast.

The features in Table 8 are comprehensive and enable me to study information content, readability, sentiment, and attention. I note several interesting patterns. First, there is significant heterogeneity between tweets posted on positive versus negative earnings surprise days. Financial news tweets receive less attention on days with negative earnings surprises than on those with positive surprises (as measured by *Likes* and *Retweets*). This suggests that on average the diffusion of good news will be faster than that of bad news. The sentiment of financial news tweets is also less positive on days with negative earnings surprises than on those with positive surprises (as measured by *Positive sentiment* and *Compound sentiment*). This result is not surprising, but it suggests that the relatively positive effects of tweeting on bad news days cannot be explained by sentiment alone. In fact, the sentiment of tweets seems to be in line with the news itself, indicating that managers are not using sentiment strategically. The measures of sentiment I use are based on a VADER (Valence Aware Dictionary for sEntiment Reasoning) model, which is sensitive to both polarity (positive/negative) and intensity (strength) of emotion and is often used in performing sentiment analysis on social media data (available at https://pypi.org/project/vaderSentiment/). *Positive* and *Negative sentiment* are the proportions of text that fall into these categories. In contrast, *Compound sentiment* is a metric that calculates the sum of all the lexicon ratings and normalizes them between -1 and 1.

Financial news tweets tend to be easier to read on days with negative earnings surprises than on days with positive ones, as measured by *Readability Index*, *Word count*, *Characters*, and *Difficult words*. These metrics show that financial news tweets about negative surprises tend to be shorter, to contain fewer difficult words, and to be overall easier to understand. The *Readability Index* is a consensus score based on the most common methods for calculating the grade level of a text (available at https://pypi.org/project/textstat/). A score of 9.2, for instance, means that a ninth grader would typically be able to read the text.

Table 9 shows the 60 most common unigrams and bigrams in the corpus of financial news tweets. The tweets are divided into two groups, those posted on positive earnings surprise days and those posted on negative surprise days. The total frequency of appearance of each word in positive and negative earnings surprise tweets and the average frequency per tweet are reported. I note several interesting differences between financial news tweets on positive and negative announcement days.

First, financial news tweets are significantly less likely to mention "EPS" (earnings per share) on days with negative earnings surprises than positive surprise days. This result is particularly interesting because of the definition of negative news, in which actual EPS is compared to the market's expected EPS. Also, EPS is one of the most important numbers released during quarterly and annual announcements, attracting analysts' attention and media coverage. This result suggests that firms use discretion when announcing financial news on social media and are less likely to disseminate an unfavorable metric.

Second, financial news tweets are twice as likely to mention "dividends" on days with negative earnings surprises than positive surprise days. Like earnings per share, dividends are closely watched by investors and communicate the financial well-being of a firm. This result suggests that firms may use Twitter to republicize "good news" on days when their earnings results are poor.

Table 10 shows the 60 most common unigrams and bigrams in the remaining tweets in my sample. There is significant heterogeneity between tweets posted on positive earnings surprise days and negative surprise days. In comparison to Table 9, the average frequency of terms per tweet is much lower, this is to be expected, as these tweets span a wider range of topics than the financial news tweets.

Table 8: Features of Tweets

This table provides a mean comparisons of statistics from tweets when firms have a negative or positive earnings surprise. I test for differences in means using a t-test. *, **, and *** indicates significance at the 10%, 5%, and 1%, respectively.

	Additional Tweets			**Financial News Tweets**		
	Pos Surprise	*Neg Surprise*	Δ	*Pos Surprise*	*Neg Surprise*	Δ
	(1)	(2)	(3)	(4)	(5)	(6)
Likes	40.166	37.248	-2.918	7.23	4.16	-3.070***
Retweets	22.549	17.197	-5.352	3.809	2.597	-1.212***
URL	0.753	0.728	-0.024***	0.848	0.864	0.017*
Picture	0.401	0.385	-0.016***	0.145	0.118	-0.027***
User tags	0.442	0.437	-0.004	0.132	0.116	-0.016
Hashtags	0.896	0.919	0.023**	0.482	0.405	-0.077***
Percentages	0.034	0.032	-0.002	0.152	0.127	-0.025**
Dollar amounts	0.029	0.035	0.007***	0.157	0.153	-0.004
Negative sentiment	0.028	0.026	-0.002***	0.011	0.012	0.001
Positive sentiment	0.151	0.158	0.007***	0.074	0.066	-0.008**
Compound sentiment	0.248	0.267	0.019***	0.150	0.130	-0.021**
Readability Index	8.835	8.645	-0.189***	9.208	8.992	-0.216**
Word count	13.789	13.818	0.028	14.923	14.406	-0.516***
Characters	89.182	88.843	-0.340	97.072	94.090	-2.981**
Difficult words	3.751	3.579	-0.173***	4.468	4.330	-0.138**
Syllables per word	1.665	1.650	-0.015***	1.667	1.675	0.008

Table 9: Financial news tweets: Term frequency

This table provides a mean comparisons of statistics from tweets when firms have a negative or positive earnings surprise. I test for differences in means using a t-test. *, **, and *** indicates significance at the 10%, 5%, and 1%, respectively.

		Positive Earnings Surprise		Negative Earnings Surprise		
Order	Common Terms	Frequency	Per tweet	Frequency	Per tweet	Δ
(1)	(2)	(3)	(4)	(5)	(6)	(7)
1	earnings	4343	0.47	1147	0.45	-0.020
2	results	3831	0.41	1156	0.45	0.039***
3	quarter	2957	0.38	923	0.43	0.046***
4	reports	1980	0.21	640	0.25	0.037***
5	year	1074	0.18	328	0.20	0.023*
6	financial	1275	0.14	382	0.15	0.012
7	financial results	950	0.10	292	0.11	0.012
8	today	746	0.09	204	0.10	0.007
9	webcast	797	0.09	227	0.09	0.002
10	sales	773	0.08	187	0.07	-0.010
11	second quarter	601	0.08	170	0.08	0.000
12	growth	716	0.08	139	0.05	-0.022***
13	ceo	713	0.08	167	0.07	-0.011
14	revenue	710	0.08	150	0.06	-0.018**
15	eps	698	0.08	119	0.05	-0.029***
16	conference	648	0.07	131	0.05	-0.019***
17	announces	645	0.07	267	0.10	0.035***
18	release	642	0.07	175	0.07	-0.001
19	fiscal	591	0.06	181	0.07	0.007
20	net	586	0.06	140	0.06	-0.008
21	fourth quarter	472	0.06	195	0.09	0.030***
22	strong	572	0.06	97	0.04	-0.023***
23	share	551	0.06	160	0.06	0.002
24	live	501	0.06	141	0.06	0.001
25	record	476	0.05	68	0.03	-0.026***
26	quarter results	798	0.05	259	0.05	-0.003
27	billion	471	0.05	103	0.04	-0.010
28	tomorrow	432	0.05	99	0.04	-0.007
29	join	1469	0.05	526	0.04	-0.001
30	million	409	0.04	153	0.06	0.016**
31	income	381	0.04	123	0.05	0.006
32	listen	385	0.04	129	0.05	0.009
33	reported	358	0.04	113	0.04	0.005
34	earnings conference	352	0.04	86	0.03	-0.004
35	guidance	347	0.04	91	0.04	-0.002
36	operating	343	0.04	90	0.04	-0.001
37	revenues	320	0.04	63	0.03	-0.010*
38	quarter year	196	0.04	85	0.05	0.015***
39	read	320	0.03	103	0.04	0.006
40	quarter earnings	387	0.03	126	0.04	0.005
41	adjusted	260	0.03	70	0.03	-0.001
42	earnings results	268	0.03	89	0.03	0.006
43	net income	255	0.03	74	0.03	0.001
44	cfo	249	0.03	71	0.03	0.001
45	performance	247	0.03	36	0.01	-0.012***
46	details	242	0.03	76	0.03	0.004
47	learn	241	0.03	44	0.02	-0.009*
48	press release	237	0.03	75	0.03	0.004
49	grew	236	0.03	34	0.01	-0.012***
50	increased	235	0.03	55	0.02	-0.004
51	announced	233	0.03	82	0.03	0.007
52	diluted	231	0.03	33	0.01	-0.012***
53	business	213	0.02	62	0.03	0.002
54	fiscal year	195	0.02	65	0.03	0.005
55	cash	191	0.02	69	0.03	0.006
56	dividend	191	0.02	95	0.04	0.016***
57	fy	639	0.01	152	0.01	0.000
58	quarter financial	297	0.01	84	0.01	0.000
59	fullyear	345	0.00	99	0.00	0.000
60	nongaap	282	0.00	42	0.00	0.000

Table 10: Additional tweets: Term frequency

This table provides a mean comparisons of statistics from tweets when firms have a negative or positive earnings surprise. I test for differences in means using a t-test. *, **, and *** indicates significance at the 10%, 5%, and 1%, respectively.

		Positive Earnings Surprise		Negative Earnings Surprise		
Order	Common Terms	Frequency	Per tweet	Frequency	Per tweet	Δ
(1)	(2)	(3)	(4)	(5)	(6)	(7)
1	new	4888	0.06	1540	0.06	-0.004*
2	learn	3226	0.04	973	0.04	-0.004**
3	today	2462	0.04	899	0.04	0.005**
4	help	2321	0.03	758	0.03	-0.001
5	day	1991	0.03	736	0.03	0.003**
6	check	1871	0.02	672	0.03	0.002
7	ceo	1785	0.02	404	0.02	-0.007***
8	make	1575	0.02	508	0.02	-0.001
9	business	1572	0.02	492	0.02	-0.001
10	time	1572	0.02	543	0.02	0.001
11	know	1543	0.02	515	0.02	0.000
12	great	1518	0.02	563	0.02	0.002*
13	data	1457	0.02	446	0.02	-0.002
14	join	1453	0.02	514	0.02	0.001
15	read	1394	0.02	480	0.02	0.001
16	need	1369	0.02	394	0.02	-0.003**
17	growth	1308	0.02	327	0.01	-0.004***
18	best	1241	0.02	437	0.02	0.001
19	video	1189	0.02	358	0.01	-0.002
20	like	1185	0.02	416	0.02	0.001
21	watch	1162	0.02	321	0.01	-0.002**
22	booth	1127	0.02	447	0.02	0.003**
23	team	1120	0.02	361	0.01	0.000
24	thanks	1093	0.01	369	0.01	0.000
25	look	1082	0.01	414	0.02	0.002*
26	work	1051	0.01	345	0.01	-0.001
27	week	1050	0.02	426	0.02	0.004***
28	want	1034	0.01	345	0.01	0.000
29	tech	1004	0.01	275	0.01	-0.003***
30	live	1000	0.01	283	0.01	-0.002*
31	win	1000	0.01	394	0.02	0.002**
32	digital	996	0.01	314	0.01	-0.001
33	use	967	0.01	337	0.01	0.000
34	home	953	0.01	371	0.02	0.002*
35	visit	909	0.01	295	0.01	0.000
36	future	905	0.01	278	0.01	-0.001
37	tips	891	0.01	380	0.02	0.003***
38	technology	881	0.01	239	0.01	-0.002**
39	share	873	0.01	286	0.01	0.000
40	global	856	0.01	288	0.01	0.000
41	customers	846	0.01	281	0.01	0.000
42	good	846	0.01	336	0.01	0.002*
43	market	843	0.01	335	0.01	0.002**
44	job	840	0.01	314	0.01	0.001
45	world	828	0.01	253	0.01	-0.001
46	happy	827	0.01	320	0.01	0.002*
47	years	818	0.01	242	0.01	-0.001
48	love	813	0.01	356	0.01	0.003***
49	latest	807	0.01	234	0.01	-0.001
50	free	795	0.01	301	0.01	0.001
51	blog	794	0.01	265	0.01	0.000
52	cloud	792	0.01	291	0.01	0.001
53	support	780	0.01	235	0.01	-0.001
54	energy	779	0.01	337	0.01	0.004***
55	health	775	0.01	228	0.01	-0.001
56	security	774	0.01	240	0.01	-0.001
57	did	766	0.01	260	0.01	0.000
58	looking	766	0.01	273	0.01	0.000
59	way	766	0.01	263	0.01	0.000
60	people	762	0.01	227	0.01	-0.001

5. Robustness

In this section I report the results of various robustness tests confirming the results in this paper. I show that the relationship between tweeting and announcement returns is robust to method used to determine unexpected earnings is defined, to the sample selection, and to additional fixed effect specifications.

A potential concern is that I overlook important information by using the dummy variable *Negative Surprise* rather than the continuous variable *SUE*. Both variables measure the surprise of the earnings announcement relative to the market's expectations. *Negative Surprise* is equal to one when a firm announces earnings below the analyst consensus forecast, and zero otherwise. *SUE* is the firm's actual earnings minus the analyst consensus forecast of earnings, standardized by the standard deviation of analyst forecasts.

Figure 4 shows the distribution of standardized unexpected earnings across the sample. In Table 11, I replace *Negative Surprise* with *SUE* and re-estimate equation (2). The coefficient on the interaction term *SUE * Fin News Tweet Impact* is negative and significant across specifications. This suggests that the price response to financial news tweets depends on how positive or negative the quarterly announcement is. These results are consistent with the main analysis.

In Table 12, I replace *Negative Surprise* with three bins that capture the distribution of *SUE*. I split the sample into quartiles by *SUE* and define the variables *Quartile 1*, *Quartile 2*, and *Quartile 3*. Each of these variables is equal to 1 when a firm's *SUE* is in that quartile of the distribution, and zero otherwise. *Quartile 4* is the omitted (reference) group. The coefficient on the interaction term *Q1* × *Fin News Tweet Impact* is positive and significant at 1% across specifications. The coefficients on the interaction terms *Q2* × *Fin News Tweet Impact* and *Q3* × *Fin News Tweet Impact* are also positive and significant; however, when the dummy coefficient is added to the interaction term, the full effects are insignificant. At the bottom of the table I show the results of an F-test. These results are consistent with the main analysis.

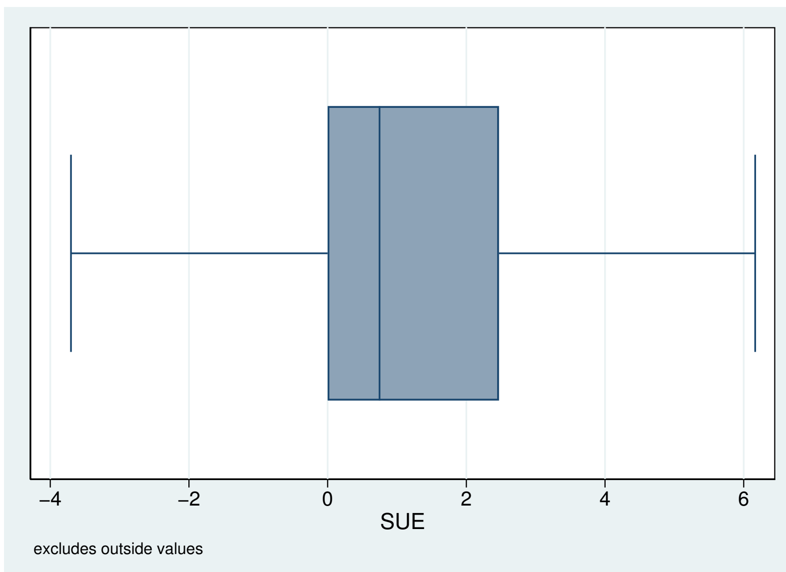


Figure 4: Box-plot of standardized unexpected earnings This figure depicts the distribution of standardized unexpected earnings (SUE) in my sample.

Table 11: Tweeting and Announcement Returns

This table shows the relationship between cumulative abnormal returns, $CAR_{[-1,1]}$, and a firm's tweeting behavior. The dummy variable *Negative Surprise* is replaced by the continuous variable *SUE*, standardized unexpected earnings. In columns (1) and (2) *FinNewsTweetImpact* is measured as *FinNewsTweets*, in columns (3) and (4) as *FinNewsTweets*Retweets*. To mitigate the influence of outliers, all continuous variables are winsorized at the 1st and 99th percentiles. Standard errors are clustered at the firm level and provided in parentheses beneath the coefficient estimates. *, **, and *** indicates significance at the 10%, 5%, and 1%, respectively.

	CAR			
	(1)	(2)	(3)	(4)
SUE	0.703***	0.767***	0.703***	0.737***
	(0.028)	(0.034)	(0.028)	(0.031)
Fin News Tweet Impact	0.283*	0.414***	0.076	0.236***
	(0.149)	(0.153)	(0.075)	(0.082)
*SUE * Fin News Tweet Impact*		-0.123***		-0.076***
		(0.039)		(0.016)
Additional Tweet Impact	0.048	0.057	0.055	0.047
	(0.083)	(0.085)	(0.083)	(0.035)
Residual ESV (Ryans)	-0.421	-0.409	-0.421	-0.429
	(0.288)	(0.289)	(0.288)	(0.289)
Size	-2.610***	-2.606***	-2.615***	-2.626***
	(0.422)	(0.442)	(0.422)	(0.421)
Loss	-1.826***	-1.733***	-1.837***	-1.802***
	(0.305)	(0.335)	(0.305)	(0.304)
BM	7.096***	7.384***	7.076***	7.084***
	(0.756)	(0.767)	(0.753)	(0.752)
Q4	0.336	0.153	0.333	0.325
	(0.208)	(0.225)	(0.208)	(0.207)
Firm FE	Yes	Yes	Yes	Yes
Quarter-year FE	Yes	Yes	Yes	Yes
F-test statistic: $\beta 2 + \beta 3 = 0$		4.117**		4.226**
F-test p-value		0.043		0.040
No. of firms	1067	1054	1067	1067
Adjusted R^2	0.127	0.143	0.126	0.128
Observations	14,222	13,170	14,222	14,222

Table 12: Tweeting and Announcement Returns: SUE Quartiles

This table shows the relationship between cumulative abnormal returns, $CAR_{[-1,1]}$, and a firm's tweeting behavior. The variable *Negative Surprise* is replaced by three variables, *Quartile 1*, *Quartile 2*, and *Quartile 3*. Each of these variables is a equal to 1 when a firm's standardized unexpected earnings, *SUE*, is in that quartile of the distribution and equal to zero otherwise. In columns (1) and (2) *FinNewsTweetImpact* is measured as *FinNewsTweets*, in columns (3) and (4) as *FinNewsTweets*Retweets*. To mitigate the influence of outliers, all continuous variables are winsorized at the 1st and 99th percentiles. Standard errors are clustered at the firm level and provided in parentheses beneath the coefficient estimates. *, **, and *** indicates significance at the 10%, 5%, and 1%, respectively.

	CAR			
	(1)	(2)	(3)	(4)
Fin News Tweet Impact	0.291**	-0.302	0.073	0.069
	(0.146)	(0.204)	(0.073)	(0.159)
Quartile 1 (SUE)	-7.100***	-7.672***	-7.105***	-7.398***
	(0.241)	(0.288)	(0.241)	(0.257)
Quartile 2 (SUE)	-3.653***	-4.049***	-3.656***	-3.822***
	(0.206)	(0.255)	(0.207)	(0.222)
Quartile 3 (SUE)	-2.354***	-2.605***	-2.358***	-2.458***
	(0.173)	(0.220)	(0.173)	(0.188)
*Q1 * FinNewsTweetImpact*		1.268***		0.607***
		(0.291)		(0.110)
*Q2 * FinNewsTweetImpact*		0.824***		0.294***
		(0.242)		(0.100)
*Q3 * FinNewsTweetImpact*		0.491**		0.157*
		(0.196)		(0.086)
Additional Tweet Impact	0.030	0.027	0.053	0.050
	(0.082)	(0.083)	(0.034)	(0.034)
Residual ESV (Ryans)	-0.435	-0.430	-0.448	-0.439
	(0.287)	(0.288)	(0.287)	(0.287)
Size	-2.355***	-2.362***	-2.374***	-2.373***
	(0.402)	(0.403)	(0.402)	(0.403)
Loss	-1.896***	-1.874***	-1.903***	-1.860***
	(0.309)	(0.308)	(0.309)	(0.309)
BM	7.070***	7.067***	7.062***	7.091***
	(0.756)	(0.756)	(0.753)	(0.755)
Fourth Quarter	0.331	0.324	0.328	0.316
	(0.203)	(0.204)	(0.203)	(0.203)
Firm FE	Yes	Yes	Yes	Yes
Quarter-year FE	Yes	Yes	Yes	Yes
F-test statistic Q1: $\beta 1 + \beta 5 = 0$		16.56***		14.99***
F-test statistic Q2: $\beta 1 + \beta 6 = 0$		6.63		5.05
F-test statistic Q3: $\beta 1 + \beta 7 = 0$		1.16		2.22
No. of firms	1067	1067	1067	1067
Adjusted R^2	0.138	0.140	0.138	0.140
Observations	14,222	14,222	14,222	14,222

In Table 13, I show that the results are robust to a pooled OLS estimation and a rich set of fixed effects. Fixed effects help to control for unobservable determinants of tweeting: quarter-year fixed effects for macro factors, and firm-year (firm) fixed effects for time-varying (time-invariant) firm characteristics. The results are generally consistent across specifications; however, the within-group estimates tend to be higher and more significant than the pooled OLS estimates.

Earnings announcement-specific characteristics can also bias the estimates. Firms may be more likely to disclose bad news on Friday than on Monday–Thursday (DellaVigna and Pollet, 2009). To control for the variation of announcements on different days, I use day-of-week fixed effects. To control for observable announcement-specific characteristics, I include the variables $SUE_{i,t}$, $Q4_{i,t}$, and $Loss_{i,t}$.

One concern is that some of the Twitter accounts I manually collected could be erroneous or fake accounts. To control for this potential problem I limit the sample to those firms with verified Twitter accounts. The verified feature on Twitter is a signal to the public that an account of public interest is authentic. Of the 1,215 accounts in my sample, 489 are verified. Table 14 shows that the subsample of verified firms yields results similar to those in section 4.B.

The relationship between tweeting and momentum in returns is robust to different momentum proxies. In Table 7 I calculate *Momentum* using both excess returns relative to 90-day T-bills and Fama-French excess returns. In Table 15, I measure momentum in three alternative ways. Following Hong et al. (2000) I use the serial correlation coefficient of six-month excess returns (relative to 90-day T-bills). I also calculate *momentum (AC)* using cumulative 3-month excess returns rather than monthly returns. *Momentum* is calculated in column (1) using 3-month excess returns relative to 90-day T-bills and in column (2) using Fama-French three-factor excess returns.

Table 13: Various Fixed Effects: Tweeting and Announcement Returns

This table shows the relationship between cumulative abnormal returns, $CAR_{[-1,1]}$, and firms' tweeting behaviors. In columns (1) and (2) *FinNewsTweetImpact* is measured as *FinNewsTweets*, in column (3) as *FinNewsTweets*Followers*, and in column (4) as *FinNewsTweets*Retweets*. To mitigate the influence of outliers, all continuous variables are winsorized at the 1st and 99th percentiles. See Appendix A for variable definitions. Standard errors are clustered at the firm level and provided in parentheses beneath the coefficient estimates. *, **, and *** indicates significance at the 10%, 5%, and 1%, respectively.

	CAR				
	(1)	(2)	(3)	(4)	(5)
Negative Surprise	-3.632***	-3.622***	-3.771***	-3.968***	-3.970***
	(0.205)	(0.206)	(0.214)	(0.243)	(0.243)
Fin News Tweet Impact	-0.193**	-0.192**	0.086	0.181	0.177
	(0.091)	(0.092)	(0.152)	(0.218)	(0.218)
*Neg Surp*Fin News Tweet Impact*	0.747***	0.727***	0.778***	0.879***	0.875***
	(0.212)	(0.211)	(0.229)	(0.251)	(0.251)
Additional Tweet Impact	-0.055	-0.067	0.044	0.091	0.106
	(0.051)	(0.052)	(0.081)	(0.110)	(0.110)
Residual ESV (Ryans)	-0.409	-0.392	-0.408	-0.599**	-0.590**
	(0.284)	(0.289)	(0.284)	(0.292)	(0.292)
SUE	0.417***	0.419***	0.464***	0.483***	0.483***
	(0.026)	(0.026)	(0.028)	(0.031)	(0.031)
Size	-0.236***	-0.228***	-2.557***	-4.818***	-4.835***
	(0.039)	(0.039)	(0.361)	(0.941)	(0.939)
Loss	-1.206***	-1.178***	-1.637***	-2.085***	-2.085***
	(0.242)	(0.243)	(0.301)	(0.346)	(0.346)
BM	1.687***	1.662***	6.873***	20.462***	20.492***
	(0.212)	(0.213)	(0.710)	(1.723)	(1.720)
Q4	0.494***	0.340	0.492***	0.397*	0.389*
	(0.144)	(0.207)	(0.143)	(0.210)	(0.210)
Quarter-year FE	No	Yes	No	Yes	Yes
Firm FE	No	No	Yes	No	No
Firm FE	No	No	No	Yes	Yes
Weekday FE	No	No	No	No	Yes
F-test statistic: $\beta 2 + \beta 3 = 0$	10.462	9.879	14.151	14.506	14.312
F-test p-value	0.001	0.002	0.000	0.000	0.000
No. of firms	1067	1067	1067	1046	1046
Adjusted R^2	0.130	0.130	0.156	0.193	0.193
Observations	14,223	14,222	14,223	13,838	13,838

Table 14: Verified Firms: Tweeting and Announcement Returns

This table shows the relationship between cumulative abnormal returns, $CAR_{[-1,1]}$, and firms' tweeting behaviors for the subsample of firms with verified Twitter accounts. In columns (1) and (2) *FinNewsTweet-Impact* is measured as *FinNewsTweets*, in column (3) as *FinNewsTweets*Followers*, and in column (4) as *FinNewsTweets*Retweets*. To mitigate the influence of outliers, all continuous variables are winsorized at the 1st and 99th percentiles. See Appendix A for variable definitions. Standard errors are clustered at the firm level and provided in parentheses beneath the coefficient estimates. *, **, and *** indicates significance at the 10%, 5%, and 1%, respectively.

	CAR			
	(1)	(2)	(3)	(4)
Negative Surprise	-3.255***	-3.619***	-3.255***	-3.530***
	(0.251)	(0.288)	(0.251)	(0.271)
Fin News Tweet Impact	0.016	-0.166	0.013	-0.059
	(0.169)	(0.179)	(0.080)	(0.082)
*Neg Surp*Fin News Tweet Impact*		0.854***		0.456***
		(0.290)		(0.114)
Additional Tweet Impact	-0.019	-0.015	-0.019	0.061
	(0.106)	(0.107)	(0.106)	(0.038)
SUE	0.501***	0.499***	0.500***	0.500***
	(0.040)	(0.040)	(0.040)	(0.040)
Residual ESV (Ryans)	-0.533	-0.536	-0.533	-0.547
	(0.398)	(0.399)	(0.398)	(0.400)
Size	-2.591***	-2.563***	-2.592***	-2.605***
	(0.604)	(0.607)	(0.604)	(0.608)
Loss	-1.774***	-1.751***	-1.772***	-1.738***
	(0.422)	(0.423)	(0.423)	(0.423)
BM	6.536***	6.562***	6.538***	6.583***
	(1.199)	(1.196)	(1.201)	(1.204)
Q4	0.597**	0.582**	0.597**	0.588**
	(0.270)	(0.270)	(0.270)	(0.269)
Firm FE	Yes	Yes	Yes	Yes
Quarter-year FE	Yes	Yes	Yes	Yes
F-test statistic: $\beta 2 + \beta 3 = 0$		5.867		9.581
F-test p-value		0.016		0.002
No. of firms	463	463	463	463
Adjusted R^2	0.159	0.160	0.159	0.161
Observations	7,357	7,357	7,357	7,357

Table 15: Tweeting and short-term continuation in returns

This table shows the cross-sectional relationship between short-term continuation in returns and the consistency of tweeting about earnings news. The dependent variable is measured in three ways. *AC* is measured as the correlation between the series $ExRet_{i,[t,t+2]}$ and the lagged series $ExRet_{i,[t-12,t-2]}$, where $ExRet_{i,[t,t+2]}$ is the cumulative 3-month excess return of firm *i*. In column (1) *AC* is calculated using excess returns relative to 90 day T-bills and in column (2) using Fama-French three factor excess returns. In column (3) *SCC* is the serial correlation of six-month excess returns (relative to 90 day T-bills). The sample is restricted to firms with verified Twitter accounts. To mitigate the influence of outliers, all continuous variables are winsorized at the 1st and 99th percentiles. See Appendix A for variable definitions. The regression is estimated using OLS with robust standard errors. Standard errors are provided in parentheses beneath the coefficient estimates. *, **, and *** indicates significance at the 10%, 5%, and 1%, respectively.

	AC		*SCC*
	(1)	(2)	(3)
Fin News Tweet Quarters	-0.048*	-0.057**	-0.017*
	(0.025)	(0.028)	(0.009)
BM	0.024	0.039	0.023***
	(0.028)	(0.044)	(0.005)
Analysts	-0.000	-0.000	0.001*
	(0.001)	(0.002)	(0.000)
Size	0.016**	0.001	-0.003
	(0.007)	(0.010)	(0.002)
Institutional Ownership	0.003	-0.067	-0.018
	(0.084)	(0.100)	(0.024)
Twitter Followers	0.000*	-0.000	0.000
	(0.000)	(0.000)	(0.000)
Constant	-0.284***	-0.116	0.799***
	(0.099)	(0.121)	(0.027)
R^2	0.031	0.022	0.036
Observations	442	352	476

6. Conclusion

This paper examines the recent phenomenon of corporate information disclosures via social media, in which companies communicate with investors using a social network as a new voluntary communication channel. After constructing a comprehensive dataset of over 7 million tweets posted by S&P 1500 firms, I exploit firms' discretionary use of social media in disseminating quarterly earnings announcements news to explore the following research question: Do firms' disclosure strategies shape the link between corporate information dissemination on social media and stock returns?

In line with previous research, I find that firms strategically disclose quarterly announcements on social media. The evidence shows that not only do firms strategically choose when to tweet about earnings announcements, but they also strategically choose what kind of information to include in the tweets.

Further analyses indicate that firms with negative earnings surprises tend to have higher announcement returns when they tweet about their earnings announcements. This result is supported by a high-frequency analysis, which shows that when firms with negative earnings surprises tweet about financial news, their abnormal cumulative returns appreciate substantially in the 30 minutes following the tweet. These results are consistent with the theoretical prediction that the jump in expected returns associated with using a strategic disclosure strategy is stronger for firms which announce a negative earnings surprise at date 0.

The findings of this study are of importance to regulators, investors, and firms. Social media is a new disclosure channel that has gained an outreach as relevant as that of traditional information intermediaries, such as business press, newswire services, and financial analysts. Nevertheless, the choice disclose information on or withhold it from social media channels has been left to the managers' discretion. Despite the SEC's attempt to promote full and fair disclosures, the information a firm discloses on social media often reflects the strategic decisions of managers.

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Appendix

Comparison of firms with and without Twitter accounts

To determine which types of firms have a corporate Twitter account, I compare a broad set of firm characteristic along with valuation, liquidity, profitability, and financial soundness metrics by estimating the following regression:

$$\begin{aligned} TwitterDummy_{i,t} = \alpha &+ \beta_1 Size_{i,t} + \beta_2 StockMarketIndex_{i_t} + \beta_3 Valuation_{i,t} \\ &+ \beta_4 Profitability_{i,t} + \beta_5 FinancialSoundness_{i,t} \\ &+ \beta_6 IndustryChars + \beta_7 OtherRatios. \end{aligned} \tag{5}$$

In equation (5), the dependent variable, $TwitterDummy$, is a dummy equal to 1 if the firm has an active Twitter account as of October 2017. *Size* is the natural logarithm of *Total Assets*. $StockMarketIndex$ is composed of two dummy variables, *S&P 500* and *S&P 600* which indicate whether the firm was listed in the respective index. $Valuation$ is composed of the *Book to Market* and *Price to Operating Earnings* ratios. $Profitability$ is composed of the *Gross Profit Margin* and *Gross Profit to Total Assets* ratios. $FinancialSoundness$ is composed of *Capitalization*, *Cash Balance to Total Liabilities*, *Long Term Debt to Total Liabilities*, *Operating CF to Current Liabilities*, and *Asset Turnover*. $IndustryChars$ is composed of the *Research and Development over Sales*, *Advertising Expenses over Sales*, *Labor Expenses over Sales*, an indicator variable if a firm is in a manufacturing industry (*Manufacturing*), and an indicator variable if a firm is in a business-to-consumer traded industry (*B2C Traded Industry*). Finally, *OtherRatios* is composed of *Accruals over Average Assets* and *Institutional Ownership as a Percentage of Shares Outstanding*.

In Table A1, equation (5) is estimated with standard errors clustered by industry.[9] In column (1) a probit model is estimated, while in columns (2) and (3) OLS and OLS with industry fixed effects models are estimated, respectively.

[9]The three-digit North American Industry Classification System (NAICS) code is used for clustering.

On average, larger firms and, incremental to size, firms belonging to the S&P 500 index have a higher probability of having a Twitter account. This result suggests that having a Twitter account is not a substitute for overall visibility but rather a complement to it.

Firms with a lower book-to-market ratio also have a higher probability of having a Twitter account. Technology companies and other companies in industries that have fewer physical assets tend to have a low book-to-market ratio. However, this result holds when including industry fixed effects (column (3)), and therefore it appears that firms with relatively higher valuations than their industry peers are more likely to have a Twitter account.

Table A1: Firms With and Without Twitter

This table shows the relationship between the likelihood of having a corporate Twitter account and various firm characteristics. The dependent variable is a dummy variable equal to one if a firm has a Twitter account during my sample period, and equal to zero otherwise. In columns (1) the regression is estimated using a probit model, in columns (2) and (3) using an OLS model. Standard errors are clustered by industry and are provided in parentheses beneath the coefficient estimates. See Appendix A for variable definitions. *, **, and *** indicates significance at the 10%, 5%, and 1%, respectively.

	Twitter Dummy		
	(1)	(2)	(3)
Size (log of Total Assets)	0.206***	0.060***	0.064***
	(0.036)	(0.010)	(0.011)
S&P 500 (Large Cap)	0.215**	0.064*	0.071*
	(0.105)	(0.033)	(0.036)
S&P 600 (Small Cap)	0.032	-0.003	-0.005
	(0.082)	(0.030)	(0.030)
Book/Market	-0.209***	-0.067***	-0.035
	(0.070)	(0.019)	(0.022)
Price/Operating Earnings	0.000*	0.000*	0.000
	(0.000)	(0.000)	(0.000)
Gross Profit Margin	0.314**	0.066*	0.036
	(0.147)	(0.036)	(0.035)
G*ross Profit/Total Assets*	0.537***	0.171***	0.189***
	(0.206)	(0.057)	(0.057)
Capitalization Ratio	0.121	0.038	0.019
	(0.262)	(0.080)	(0.081)
Cash Balance/Total Liabilities	0.021	0.006	0.004
	(0.036)	(0.012)	(0.011)
Long-term Debt/Total Liabilities	-0.478	-0.163	-0.126
	(0.292)	(0.098)	(0.098)
Operating CF/Current Liabilities	-0.122**	-0.032**	-0.025**
	(0.058)	(0.014)	(0.011)
Asset Turnover	0.071	0.016	0.012
	(0.058)	(0.017)	(0.019)
Research and Development/Sales	0.453**	0.101*	0.061
	(0.204)	(0.051)	(0.049)
Advertising Expenses/Sales	-0.908	-0.063	-0.096
	(1.171)	(0.156)	(0.165)
Labor Expenses/Sales	0.954**	0.104*	0.056
	(0.485)	(0.053)	(0.038)
Accruals/Average Assets	0.170	0.020	0.080
	(0.371)	(0.122)	(0.128)
Institutional Ownership % Shrs Out	-0.131	-0.005	-0.043
	(0.211)	(0.070)	(0.073)
Manufacturing	-0.119	-0.050	
	(0.103)	(0.034)	
B2C Traded Service	0.153	0.038	
	(0.161)	(0.046)	
Industry FE	No	No	Yes
No. of clusters	74	74	78
Adjusted (Pseudo) R^2	(0.078)	0.085	0.159
Observations	29,584	29,584	29,774

Summary statistics

Table A2: Distribution of Tweets by Calendar Quarter

This table presents the frequency distributions of tweets and observations by calendar quarter. My sample encompasses 7,132,461 tweets posted by S&P1500 firms with active Twitter accounts as of October 2017. The sample represents represents 16,844 firm-quarters. The number of firm quarter observations increases over the sample. This pattern is to be expected because some Twitter users in the sample were not active at the start of the sample period.

Calendar Quarter	Tweets		Observations	
	N	%	N	%
2014Q1	422,377	5.4%	950	5.0%
2014Q2	428,965	5.5%	968	5.1%
2014Q3	460,574	5.9%	984	5.2%
2014Q4	501,935	6.5%	996	5.2%
2015Q1	463,611	6.0%	1,023	5.4%
2015Q2	481,138	6.2%	1,032	5.4%
2015Q3	489,600	6.3%	1,060	5.5%
2015Q4	570,359	7.3%	1,070	5.6%
2016Q1	433,123	5.6%	1,058	5.5%
2016Q2	435,102	5.6%	1,071	5.6%
2016Q3	420,817	5.4%	1,070	5.6%
2016Q4	454,652	5.9%	1,089	5.7%
2017Q1	428,492	5.5%	1,103	5.8%
2017Q2	378,364	4.9%	1,110	5.8%
2017Q3	384,522	5.0%	1,128	5.9%
2017Q4	378,830	4.9%	1,132	5.9%
All	7,132,461	100.0%	16,844	100.0%

Table A3: Tweet Characteristics

This table presents descriptive statistics related to Twitter users (firms), firm-quarters, and individual tweets. Firms have a mean (median) or 162,642 (6,352) followers. The average date firms joined Twitter was in November 2010. Firm-quarters have a mean (median) of 178 (81) tweets and 1.24 (1) tweets about earnings news. Tweets have a mean (median) of 79 (86) characters, 8 (0) retweets, and 16 (0) likes.

Variable	Mean	Std. Dev	P01	Q1	Median	Q3	P99
Per Twitter User (N = 1,215)							
Number of Followers	162,642	1,383,262	73	1,473	6,352	29,200	2,300,412
Number of Friends	2,438	9,814	0	194	557	1,535	35,626
Date Joined Twitter	Nov2010	-	Jun2007	Apr2009	Jan2007	Jan2012	May2017
Per Firm Quarter (N = 13,350)							
Tweet Count	178.00	430.00	0.00	22.00	81.00	209.00	1438.00
Quarter with Tweets	92%	0.26	0.00	1.00	1.00	1.00	1.00
Earnings Tweet Count	1.24	3.48	0.00	0.00	0.00	1.00	13
Quarter with Earnings Tweets	35%	0.48	0.00	0.00	0.00	1.00	1.00
Per Tweet (N = 7,132,461)							
Number of Characters	79.00	50.00	16.00	18.00	86.00	119.00	217.00
Number of Retweets	8.00	276.00	0.00	0.00	0.00	1.00	149.00
Number of Likes	16.00	753.00	0.00	0.00	0.00	2.00	264.00

Table A4: Summary Statistics

This table reports summary statistics for firm-quarter observations used to estimate (1) and (2), and firm-month observations to estimate (3). The sample period is from Q1 2014 to Q4 2017. See Appendix table A5 for variable definitions.

	Mean	SD	P05	Med	P95
CAR[-1, 1]	0.16	7.51	-11.58	0.19	11.85
Positive Surprise	0.72	0.45	0.00	1.00	1.00
Earnings Tweet Count [-1, 1]	0.76	1.93	0.00	0.00	4.00
Non-earnings Tweet Count [-1, 1]	2.37	1.44	0.00	2.56	4.49
*Earnings Tweet Count*Followers [-1, 1]*	7.61	20.97	0.00	0.00	40.31
*Non-earnings Count*Followers [-1, 1]*	24.05	17.44	0.00	22.89	53.78
*Earnings Tweet Count*Retweets [-1, 1]*	0.74	2.62	0.00	0.00	3.85
*Non-earnings Count*Retweets [-1, 1]*	3.16	3.90	0.00	1.88	11.21
$\mid SUE \mid$	2.58	3.06	0.00	1.60	9.03
Size	8.60	1.76	5.90	8.49	11.74
Loss	0.12	0.33	0.00	0.00	1.00
BM	0.48	0.35	0.08	0.39	1.14
Analysts	2.60	0.62	1.61	2.65	3.50
Q4	0.20	0.40	0.00	0.00	1.00
SUE (forecast sd)	1.47	3.61	-3.23	0.97	7.78
SUE (price)	0.00	0.01	-0.00	0.00	0.01
SUE (book equity)	0.00	0.01	-0.01	0.00	0.02
Earnings Tweet Count [-30, -1]	0.31	1.08	0.00	0.00	2.00
Non-Earnings Tweet Count [-30, -1]	3.15	1.60	0.00	3.40	5.35
Institutional Own.	0.85	0.14	0.60	0.86	1.05
Momentum	-10.07	12.75	-30.38	-10.84	11.21
Earnings Tweet Quarters	0.34	0.38	0.00	0.18	1.00
*Earnings Tweet Quarters*Followers*	3.14	3.68	0.00	1.48	10.63
Verified	0.42	0.49	0.00	0.00	1.00

Variable definitions

Table A5: Variable Descriptions and Data Sources

Variable	Description	Data Source
Twitter Variables		
Earnings Tweet Impact	Measured in one of two ways depending on model: (1) IHS transformation of *Financial News Tweet Count*, (2) IHS transformation of *Financial News Tweet Count* * IHS transformation of *Financial News Retweets*	Twitter
Financial News Tweet Count	Number of earnings related tweets during the windows [-1, 1] around the quarterly earnings announcement date	Twitter
Additional Tweet Impact	Measured in one of two ways depending on model: (1) IHS transformation of *Additional Tweet Count*, (2) IHS transformation of *Additional Tweet Count* * IHS transformation of *Additional Retweets*	Twitter
Additional Tweet Count	IHS transformation of total number of tweets minus the number financial news tweets during the windows [-1, 1] around the quarterly earnings announcement date	Twitter
Earnings Tweet Quarters	Proportion of quarters a firm tweets about financial news over the sample period, January 2014 to December 2017	Twitter
Twitter Verified	Indicator variable equal to one is a firm's Twitter account is verified by Twitter. When an account is verified by Twitter a blue check-mark appears next to the account name to signal the authenticity of that account.	Twitter
Earnings Announcement Variables		
CAR[-1, 1]	Carhart's cumulative abnormal return in the three day window [-1, 1] around the earnings announcement date	CRSP
Negative Surprise	Indicator variable equal to one if the firm's $SUE < 0$, and equal to zero otherwise.	IBES

SUE	The firm's actual EPS minus the consensus analyst forecast EPS, standardized by the standard deviation of analysts' consensus forecasts, by price per share of stock at the end of the quarter, or by the book value of equity per share at the end of the previous quarter. Consensus analyst forecast is measured as the median latest analyst forecast in the 90 days prior to the earnings announcement.	IBES
Firm Variables		
Size	Log of total assets (Compustat atq).	Compustat
BM	Book to market value (Compustat ceqq/mkvaltq).	Compustat
Loss	Indicator variable set to 1 if the firm reports a quarterly loss (Compustat $niq < 0$).	Compustat
Analyst	Natural log of one plus the average number of analysts following a given firm during the 90 days prior to the earnings announcement.	IBES
Q4	Indicator variable equal to one if the quarterly earnings announcement is in the fourth fiscal quarter of the year	Compustat
Institutional Ownership %	Total institutional ownership as a percentage of shares outstanding.	Thomson Reuters 13-f
Autocovariance Variables		
Autocovariance	Correlation between the series $EzRet_{[t,t]}$ and the lagged series $ExRet_{[t-12,t-2]}$, where $ExRet_{[t,t]}$ is the monthly excess return of a firm. Excess returns are calculated relative to 90 day T-bills or Fama-French three factor excess returns.	CRSP
EDGAR Log File Variables		
ESSV	Daily EDGAR Search Volume from the SEC's web server log file. Before calculating *ESV* the log files are filtered to remove downloads by computer programs following the procedure developed by Ryans (2017) or Loughran and McDonald (2017).	SEC

Financial news key words and phrases

To detect financial news tweets I use a classification scheme based on the dictionary of keywords and phrases below; each tweet is considered earnings news if it contains two or more of the terms found in the dictionary.

Financial news unigrams, bigrams, and trigrams: *announce, announces, cash flow, conference call, continuing operations, declare, declares, dividend, dividends, earnings, earnings call, earnings release, eps, financial position, financial results, fiscal, full year, gaap, growth, income, net sales, press release, profit, releases, results, revenue, sales, $"ticker of firm", 1q, 2q, 3q, 4q, q1, q2, q3, q4, qtr1, qrt2, qrt3, qrt4, 1st quarter, 2nd quarter, 3rd quarter, 4th quarter, first quarter, second quarter, third quarter, fourth quarter, quarter, qtr, qoq, fy13, fy14, fy15, fy16, fy17, fy18, fy2013, fy2014, fy2015, fy2016, fy2017, fy2018, year-over-year, year over year, yoy*

Examples of financial news tweets identified with text classifier

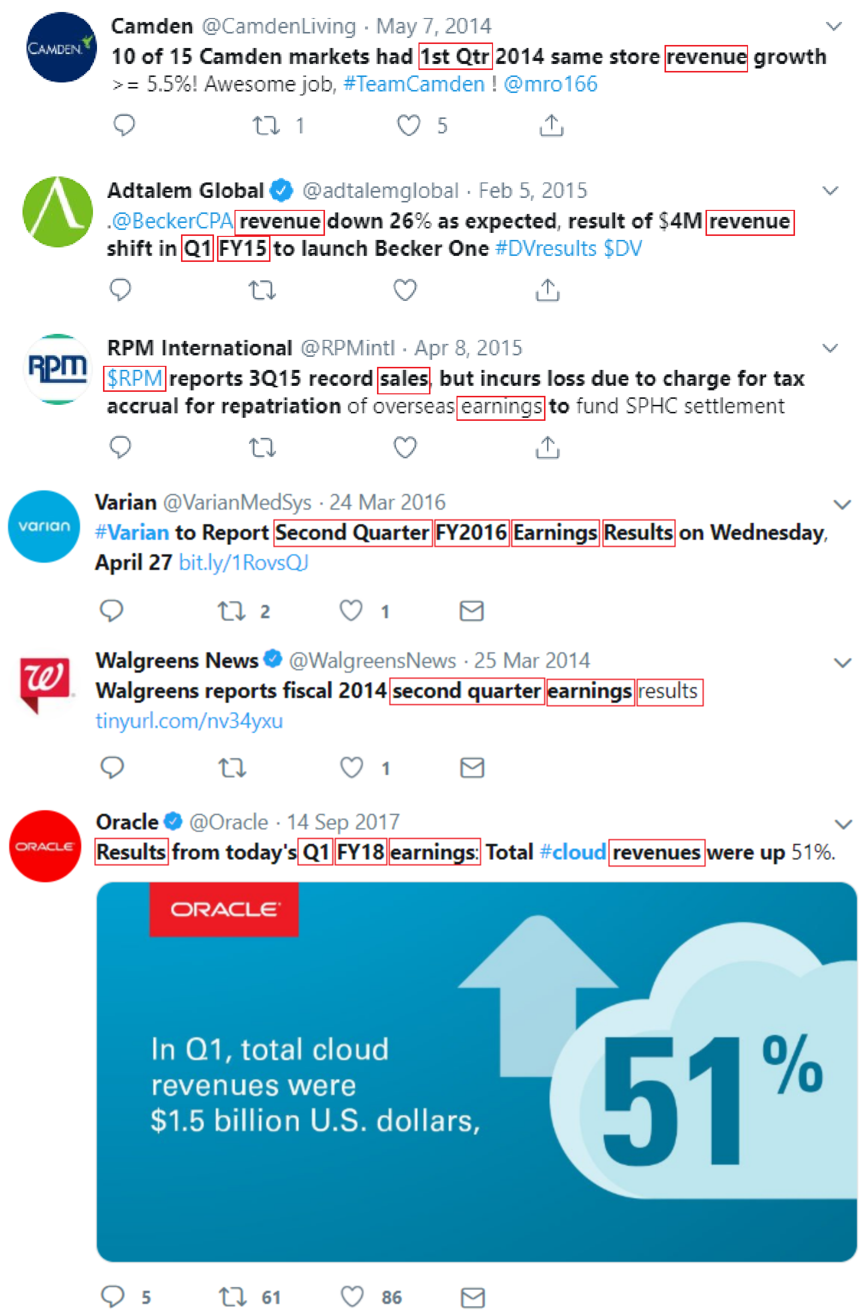

Figure 5: Tweeting around earnings announcements. This figure depicts examples of financial news tweets in my sample. Earnings announcement keywords and phrases are outlined in red. Each tweet in my sample is considered financial news if it contains two or more of the terms highlighted in red.

Theoretical model

The following equations are re-stated from Goto et al. (2009).

The firm value at date 0 is given by

$$V_0 = [\psi u + (1-\psi)d]^N, \tag{1}$$

where $\psi \equiv ru^{-\alpha}/[ru^{-\alpha} + (1-r)d^{-\alpha}]$.

When managers follow a strategic disclosure strategy (i.e., manager reports the observed number of successes, s, and zero failures at date 1) the firm value at date 1 is given by

$$V_1(s) = [\pi u + (1-\pi)d]^{N-s}, \tag{2}$$

where $\pi \equiv qu^{-\alpha}/[qu^{-\alpha} + (1-q)d^{-\alpha}]$ and $q \equiv (r - r\theta)/(1-\theta r)$.

Therefore the expected first-period return under strategic disclosure is given by

$$E[R_1(s)] = \sum_{s=0}^{N} h(s)R_1(s) = [r\theta\gamma_0 + (1-r\theta)\gamma_1]^N, \tag{3}$$

where $h(s) = \binom{N}{s}(r\theta)^s(1-r\theta)^{N-s}$ is the unconditional probability of the manager announcing s successes at date 1, $\gamma_0 \equiv u/[\psi u + (1-\psi)d] > 1$, and $\gamma_1 \equiv [\pi u + (1-\pi)d]/[\psi u + (1-\psi)d] < 1$.

When managers follow a full disclosure strategy (i.e., manager reports the observed number of successes, s, and failures, f, at date 1) the firm value at date 1 is given by

$$V_1(s,f) = [\psi u + (1-\pi)d]^{N-s-f}u^s d^f, \tag{4}$$

Therefore the expected first-period return under full disclosure is given by

$$E[R_1(s, f)] = [r\theta\gamma_3 + (1 - r\theta)]^N > 1, \tag{5}$$

where $\gamma_3 \equiv [ru + (1 - r)d]/[\psi u + (1 - \psi)d] > 1$.

Using the above equations I estimate the difference between expected first period returns when managers use a strategic disclosure strategy and when managers use a full disclosure strategy. Figure 6 shows the difference in expected returns as a function of r. When the function is monotonically decreasing this implies that the expected increase in return under strategic disclosure strategy is higher for firms which announce a negative earnings surprise at date 0 than for firms that announce positive earnings surprise. The vertical dotted line at 0.73 represents a reasonable value of r estimated in my sample, which falls in the area where the function is downward sloping.

Figure 7 shows the difference in expected returns as a function of θ. When θ increases managers are more likely to observe the outcomes of their business dimensions at $t = 1$ and asymmetric information between managers and investors is higher. Therefore, θ can be thought of as a measure of relative information asymmetry. Under reasonable parametric assumptions the model predicts that the jump in expected returns associated with using a strategic disclosure strategy is increasing in θ.

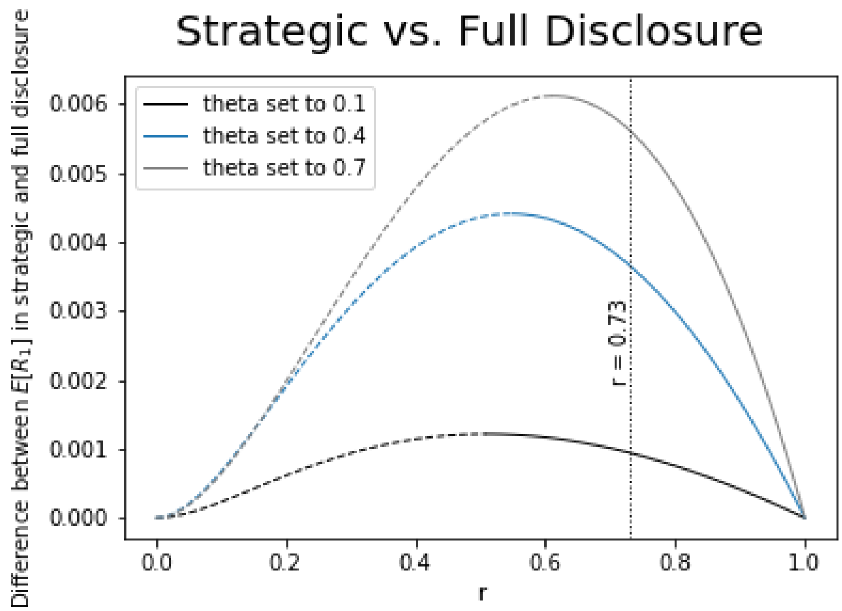

Figure 6: Difference in expected first period returns (as a function of r). This figure depicts the difference between expected first period returns when managers use a strategic disclosure strategy and when managers use a full disclosure strategy as a funciton of r, the probability a project succeeds. The other parameter values are set at $N = 100$, $u = 1.001$, $d = .99$, and $\alpha = 3$.

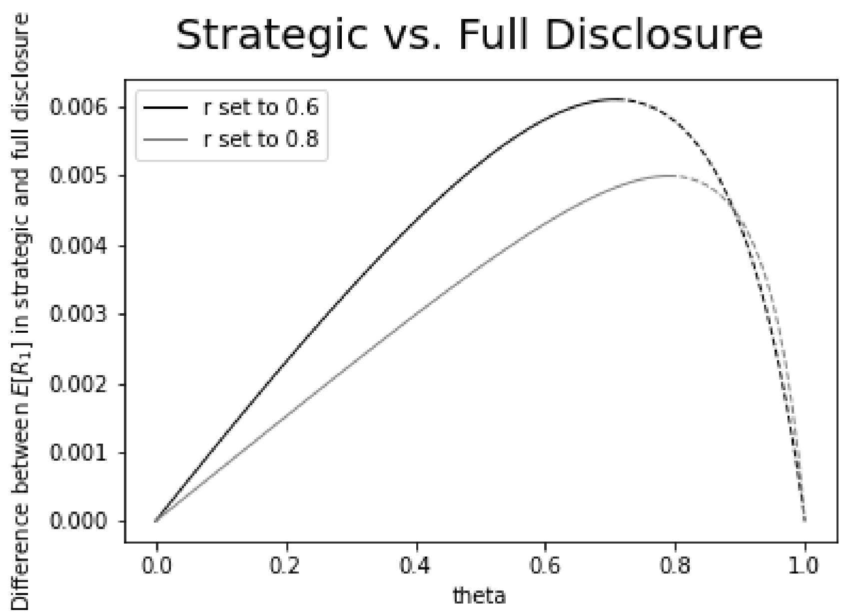

Figure 7: Difference in expected first period returns (as a function of θ). This figure depicts the difference between expected first period returns when managers use a strategic disclosure strategy and when managers use a full disclosure strategy as a funciton of r, the probability a project succeeds. The other parameter values are set at $N = 100$, $u = 1.001$, $d = .99$, and $\alpha = 3$.