SOCIAL MEDIA DISCLOSURE AND ANALYSTS AS INFORMATION INTERMEDIARIES

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ABSTRACT

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Using a sample of S&P 500 firms over the period 2012–2014 and *Twitter* data, I investigate the effect of social media disclosure on financial analysts as information intermediaries. On one hand, social media is a low-cost mechanism for direct communications from the firm to its investors, so may substitute for information intermediation by analysts. On the other hand, following Mosaic theory (Pozen, 2005), analysts (i.e., the crowd of the experts) have a comparative advantage at placing relevant pieces of information into the broader mosaic, implying that the importance of analysts as information intermediaries may increase with the volume of tweets released by the firm and by the crowd of "the public". I find firms' financial tweets are associated with larger analyst following and lower analyst forecast error. This finding is consistent with analysts using social media information as a complement to other information sources, providing richer analyses to investors. I also find that the market reaction to analysts' forecast revisions varies positively with the level of social media activity. Together, these findings suggest that social media disclosure serves as a complement to information processing by analysts, as opposed to a substitute. This paper contributes to the literature on financial analysts by providing evidence that even in the era of social media disclosure, the role of analysts as information intermediaries remains important for the efficient functioning of capital markets. It also contributes to the literature on the impact of social media on capital markets by providing a deeper understanding of the impact of unregulated and unstructured disclosure on the general information environment of financial markets.

This dissertation is dedicated to my beloved family.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

1. INTRODUCTION

Due to innovations in information technology, there have been enormous changes in firms' business communication practices over the past decade. The Internet lowered the cost of information dissemination and increased the velocity at which information travels. Similar to the introduction of the Internet, the emergence and widespread adoption of social media increased information flow by facilitating interaction between Websites and information users. The use of social media not only facilitates the dissemination of news but also encourages participation, collaboration, and information sharing (Culnan, McHuch, and Zubillaga, 2010; Chen, De, Hu, and Hwang, 2014; Kane, Alavi, Labianca, and Borgatti, 2014).

Prior research shows that social media is an efficient conduit for disseminating information to financial markets and affects investor behavior (Antweiler and Frank, 2004; Barnes, Lescault, and Wright, 2013; Lee, Hutton, and Shu, 2015; Chen, Hwang, and Liu, 2016; Bratov, Faurel, and Mohanram, 2017). However, there is limited evidence on how social media affects sophisticated information intermediaries such as financial analysts. A firm's direct communication with investors through social media may substitute for analysts' information dissemination activities. But, the same communication may also complement the information processing activities of analysts, who have a comparative advantage in positioning bits of information in the broader information mosaic (Pozen, 2005; Yeldar, 2012). Lehavy, Li, and Merkley (2011), Cao, Keskek, Myers, and Tsang (2014), and Lev and Gu (2016), for example, argue that the increased volume and complexity of firms' required disclosures to external users implies an expansion in the role of financial analysts as intermediaries. Thus, the net effect of social media disclosure on the importance of analysts as information intermediaries is an open question that I address in this paper.

I use a sample of S&P 500 firms over the period 2012-2014 and Twitter data to examine whether tweets by and about a firm are associated with analyst following, properties of analyst forecasts, and the magnitude of the market reaction to analyst forecast revisions. I measure the amount of social media disclosure by the firm as the number of tweets from the Twitter account that is linked to the firm's Website and the amount of social media disclosure about the firm by the public as the number of tweets that contain the firm's Cashtag. [1] I further split tweets by the firm into those that discuss financial topics and those that do not.

My results indicate that analyst following is larger and forecast errors are smaller, the larger the number of financial tweets by the firm. Analyst following is smaller, the larger the number of nonfinancial tweets by the firm. Forecast errors are larger, the larger the number of tweets by the public, while the volume of tweets by the public is not significantly associated with analyst following. Forecast dispersion is not significantly associated with social media disclosure. Collectively, these findings suggest that only financial social media disclosure provides timely, value-relevant information to analysts.

One interpretation of these results is that financial tweets by the firm reflect supply-side factors of information. When more information is supplied by the firm, analyst following is larger and analyst forecasts are more accurate. In contrast, tweets by the public reflect the demand for information. But, demand for information, per se, does not imply more accurate forecasts. In fact, forecasts are less accurate when the volume of public tweets is large, implying that analysts may

[1] Cashtags are stock ticker symbols that are prefixed with a dollar sign. For example, tweets about Microsoft would use $MSFT.

rely on misleading information released by the public or that demand is higher when investors' beliefs are heterogeneous.

I also report evidence on the relation between social media and the market response to analyst forecast revisions. In this analysis, I regress cumulative abnormal returns (CARs) over the two-day window beginning with the revision release date on the average analyst forecast revision, the number of financial tweets by the firm over the revision period and the interaction between the revision and the number of financial tweets by the firm. The coefficients on the revision variable and the interaction term are both positive and significant. In contrast, the coefficient on financial tweets is insignificant. Consistent with prior research (Brown, Foster, and Noreen, 1985; Klein, 1990; Lys and Sohn, 1990; Beyer, Cohen, Lys, and Walther, 2010), the positive coefficient on the revision variable indicates that revisions contain value relevant information about the firm's future cash flows. The positive coefficient on the interaction term indicates that revisions are more informative, the larger the number of financial tweets released by the firm. The coefficient on the number of tweets is insignificant, consistent with the previous impounding of the information in those tweets.

To validate the main model results and to provide enhanced perspectives about the main findings, I re-analyze the impact of social media on financial analysts as information intermediaries for subsamples of firms that are members of consumer-oriented industries and non-consumer-oriented industries.[2] In these supplemental subsample analyses, I consistently find that financial tweets by the firm provide additional value relevant information for financial analysts.

[2] Social media disclosure focuses jointly on investors and consumers, so often includes both financial information and advertising. While the difference in audience can increase the risk of misinterpretation, nonfinancial information such as advertising has the potential to engage investors as well (Madsen and Niessner, 2016).

Further, for firms in consumer-oriented industries, I also find that nonfinancial tweets by the firm provide value relevant information for financial analysts.

I also re-run the market response tests. To examine the sensitivity of my main results to the length of my event window, I regress CARs over the three-day window centered on the revision release date on the average analyst forecast revision, the number of financial tweets by the firm over the revision period, and the interaction between the revision and the number of financial tweets by the firm.

To control for the effect of management forecasts issued between forecast revisions, I also re-estimate the return analysis for subsamples of observations with and without a prior management forecast between the previous and the current forecast revisions.[3] In the two additional sensitivity analyses, I consistently find that the interaction between the forecast revision and the number of financial tweets has a positive and significant coefficient. These results indicate that revisions are more informative, the larger the number of financial tweets released by the firm and imply that social media disclosure supplements the information used by financial analysts. From this analysis, I also find that financial tweets have a larger impact on forecast revisions in the absence of concurrent management forecasts. This finding may indicate that investors rely more on financial information shared through social media by firms when there is less information from management in other formats such as management forecasts.

My findings make at least two contributions to the literature. First, I address the question: Does the rise of social media imply that traditional intermediaries are less relevant? Evidence that the market response to analyst forecast revisions is increasing in the number of financial tweets

[3] Baginski and Hassell (1990) find that prior earnings forecasts by management influence subsequent financial analyst forecast revisions.

released by the firm suggests that social media disclosure serves as a complement to information processing by analysts, as opposed to a substitute. Investors respond to the information in social media disclosures when those disclosures are released (Zhang, Fuehres, and Gloor, 2011; Bollen, Mao, and Zeng, 2011; Ruiz, Hristidis, Castillo, Gionis, 2012; Mao, Wei, Wang, and Liu, 2012; Sprenger, Tumasjan, Sandener, and Welpe, 2014), but also benefit from the subsequent interpretation of those disclosures by analysts. One explanation is that when the volume of social media disclosure by a firm is large, the ability of analysts to fit pieces of information into the overall mosaic is particularly valuable.

Second, I provide evidence consistent with the argument that social media disclosure provides timely, value-relevant information to analysts. Prior studies show that social media is an efficient conduit for disseminating information to financial markets and affects investor behavior. However, there is limited evidence on how information from social media affects the behavior and beliefs of sophisticated information intermediaries. To my knowledge, this is also the first study to examine concurrently the influence of social media disclosures by firms and the public on financial analyst following and the properties of analyst earnings forecasts.

The rest of the paper is organized as follows. Section 2 presents institutional background, summarizes related studies on social media disclosure and financial analysts, and develops hypotheses. Section 3 describes the data collection method and provides an outline of the research design. Section 4 presents results from empirical analyses of the effect of social media disclosure on analyst following and properties of analyst forecasts. This Section also includes a discussion of analysis of the relation between social media disclosures and the information content of analyst forecast revisions. Section 5 presents results of sensitivity analyses. Section 6 summarizes the main findings and provides a conclusion.

2. BACKGROUND AND HYPOTHESES

I begin this chapter by discussing the role of information technology in corporate disclosure. I then discuss changes in Regulation Fair Disclosure (Reg. FD) in response to the increased importance of social media business communication. Then, I discuss prior literature on the effect of general social media and Twitter on firms' business communication. Next, I discuss prior literature on the role of financial analysts as information intermediaries. Finally, I develop my hypotheses.

2.1. Role of Information Technology in Corporate Disclosure

Due to innovations in information technology, there have been enormous changes in firms' business communication practices over the past decade. The Internet lowered the cost of information dissemination and increased the velocity at which information travels. Ashbaugh, Johnstone, and Warfield (1999) and Ettredge, Richardson and Scholz (2002) document that most firms use the Internet for voluntary financial information disclosure. Similar to the introduction of the Internet, the emergence and widespread adoption of social media increased information flow by facilitating interaction between Websites and information users. The use of social media not only facilitates the dissemination of news but also encourages participation, collaboration, and information sharing (Culnan et al., 2010; Chen et al., 2014; Kane et al., 2014).

Social media has also reduced users' information acquisition costs. For example, firms can use social media to reduce information asymmetry by disseminating news directly to investors rather than relying solely on third party intermediaries (Blankespoor, Miller, and White, 2013). Blankespoor et al. (2013) emphasize the 'push' technology feature of social media, where push technology refers to electronic communication in which the sender transmits information to the user instead of waiting until the user specifically requests the information. They show that by sending investors a hyperlink to a press release concurrent with the issuance of the press release, firms broadly disseminate information in a timely manner and reduce investors' information acquisition costs. This broad dissemination also increases the likelihood that all users have access to the information at the same time.

2.2. Changes in SEC Disclosure Regulation

The proliferation of company Websites led the SEC to issue "Commission Guidance on The Use of Company Websites" in August 2008, which addressed how Website disclosures could qualify as "public disclosure" under Reg. FD.[4] Although social media can be used to disseminate information to a large number of users at a low cost, prior to April 2, 2013, the SEC's concerns about selective disclosure prohibited companies from using social media such as Twitter to initially disclose material and nonpublic information under Reg. FD. Therefore, rational information users could ignore social media platforms as an outlet for new information.

On April 2, 2013, the SEC responded to public companies' growing use of social media by issuing a report stating that initial dissemination of mandatory filings by SEC registrants through social media outlets such as Facebook and Twitter does not violate Reg. FD, so long as investors have been alerted in advance to the social media outlets that will be used.[5] In addition, the Commission's August 2008 "Guidance on the Use of Company Websites for Disclosure" can be applied to social media platforms. If the information is disseminated in a manner "reasonably

[4] Thus, research prior to the 2008 expansion of Reg. FD to Websites studied Internet financial disclosures that were already available from other sources. Ashbaugh et al. (1999) study corporate Website disclosure of comprehensive financial statements and links to SEC filings. Ettredge et al. (2002) examine information already filed with the SEC and other voluntary information available from other sources such as stock price, calendar events, and a list of analysts who cover the firm.

[5] Report of Investigation Pursuant to Section 21(a) of the Securities Exchange Act of 1934: Netflix, Inc., and Reed Hastings, Release No. 34-69729 (April 2, 2013) (the "21(a) Report"). (available at: https://www.sec.gov/litigation/investreport/34-69279.pdf)

designed to provide broad, non-exclusionary distribution of the information to the public", then issuers would be allowed to elect not to file a Form 8-K.

Shortly after the SEC report was issued, many companies, including Netflix, Nielson, Dell, and AutoNation, filed a Form 8-K detailing their intent to disseminate investor information on their social media feeds. As of 2013, Twitter, Facebook, and YouTube accounts were used to release corporate information by 77%, 70%, and 69% of Fortune 500 companies, respectively (Barnes et al., 2013). Therefore, rational investors are expected to pay greater attention to social media platforms as a source of new, relevant information.

As social media became more prevalent, many firms created written social media policies. Barnes and Daubitz (2017) document that 50% of Inc. 500 companies have a written social media policy incorporated into their business plan, and 21% have a stand-alone social media policy. [6] In total, 77% of Inc. 500 companies adopted social media policies to guide the online communications of the firm and its employees. Socialmediagovernance.com provides a social media policy database that includes links to each firm's social media guidelines.[7] For example, Apple provides retail blogging and online social media guidelines for its employees, and Cisco offers an Internet postings policy. Accounting and consulting firms also provide services to guide firms' social media risk management (Ernst & Young, 2014; Deloitte Touche Tohmatsu, 2015; KPMG, 2015; PwC, 2017). The policies cover both firms and their executives, including legal and regulatory compliance risk, security risk, and reputational risk (Elliot, Grant, and Hodge, 2018).

[6] Inc. is an American weekly magazine that publishes news about small businesses and startups. Beginning in 1982, the magazine publishes annual lists of the 500 and 5000 fastest-growing privately held small companies in the U.S., called the "Inc. 500" and "Inc. 5000".

[7] http://socialmediagovernance.com/policies/

2.3. Research Related to the Effect of Social Media on Firms' Business Communication

One distinctive feature of social media is that new platforms allow users to create and disseminate their own content about firms (Miller and Skinner, 2015). Users formerly known as the audience, i.e., consumers of information, are now producers of information (Rosen, 2006; Kaplan and Haenlein, 2010). For example, using a measure of the bullishness of messages posted on 'Yahoo! Finance' and 'Raging Bull', Antweiler and Frank (2004) find that stock messages help predict market volatility and that disagreement among the posted messages is associated with increased trading volume. Das and Chen (2007) find that investor sentiment extracted from Internet stock message boards is significantly related to stock indices, trading volume, and volatility. Rickett (2016) find that the financial blog, SeekingAlpha.com, serves an infomediary role for retail investors especially when information asymmetry is high, earnings quality is low, and during economic uncertainty.

Prior literature also examines the impact of social media disclosures provided by a broad set of stakeholders on the investment decisions of investors. Gomez-Carrasco and Michelon (2017) investigate the influence of social media activism on the stock market performance of targeted firms. They focus on information published on Twitter by consumer associations and trade unions. They provide evidence that tweeting by key stakeholders has a significant impact on investors' decisions. Tang (2018) finds that third-party-generated comments about products and brands on Twitter, aggregated at the firm level, provide information that is useful in forecasting firm-level fundamentals. She finds that Twitter comments not only reflect upcoming sales, but also capture an unexpected component of sales growth. The findings of this study suggest that user generated nonfinancial information on social media is also predictive of future firm performance.

The advent of social media also provides opportunities for individual public opinions about firms to be more easily accessed and aggregated (Hales, Moon, and Swenson, 2018). Recent research suggests that various platforms provide channels for communicating information that is relevant to forecasting firms' future performance and disclosure. Using crowdsourced forecast data from Estimize in 2012 and 2013, Jame, Johnston, Markov, and Wolfe (2016) find that crowdsourced forecasts are incrementally useful in forecasting earnings and measuring the market's expectations of earnings. Hales et al. (2018) examine whether the opinions employees share on social media relate to future corporate disclosures. Using a sample of approximately 150,000 employee reviews from Glassdoor.com, where employees voluntarily share their opinions on a number of issues, including the company's near-term business outlook, they find that employee opinions posted on social media platforms are useful in predicting firms' future voluntary disclosures. Together, these studies imply that users formerly known as the audience use social media disclosures to create and disseminate their own content about firms (Rosen, 2006; Miller and Skinner, 2015).

Another distinctive technological feature of social media is that it is a two-way communication channel that allows stakeholders to interact with managers and with each other (Cade, 2018; Elliott, Grant, and Hobson, 2017). Thus, social media implies a fundamental change in the information environment. Trinkle, Crossler, and Bélanger (2015) examine the impact of stakeholder comments on investors' perceptions and reactions to voluntary disclosures on social media. They find that the opinions of others, as expressed in attached comments via social media, have valuation judgments and influence investors' perceptions. The findings of this study also imply that social media not only provides two-way interaction between management and non-management stakeholders, but also results in more active interaction among non-management stakeholders. Using Twitter comments that contain product information, Tang (2018) finds that third-party-generated comments about products and brands on social media, when aggregated at the firm level, provide information that is useful in forecasting future firm sales.

Social media also provides firms with the opportunity to respond to comments and questions posted by stakeholders. This feature provides firms with the opportunity to mitigate reputational damage by engaging in conversations on Twitter. Accounting and consulting firms who provide guidance on firms' social media disclosure policies recommend that firms mitigate social media risk by monitoring social media conversations and responding quickly when issues emerge. Recent research supports this guidance (Elliot et al., 2018). Lee et al. (2015) examine how corporate social media affects the capital market consequences of consumer product recall disclosures. They find that during a crisis triggered by a recall, quickly informing customers and the public of the recall on social media helps to minimize the spread of rumors and misinformation. They document that corporate social media, on average, attenuates the negative price reaction to recall announcements, and that the attenuation benefits vary with the level of firm involvement and with the level of control the firm has over its social media content.[8] Gans, Goldfarb, and Lederman (2017) find that customer complaints on Twitter increase when the on-time performance of airlines deteriorates, and that airline companies are more likely to respond to the complaints if the complaints are from airports or hubs out of which they operate a greater share of flights. This paper suggests that two-way communication using social media also plays a disciplining role by improving firms' service or product quality. Cade (2018) examines how a firm's social media

[8] Hsu and Lawrence (2016) also investigate how company involvement in social media affects the capital market consequences of firms' disclosure in the context of product recalls. Surprisingly, they find no effect of company involvement in mitigating the potential negative effects of social media during a product recall. Hsu and Lawrence's (2016) sample covers not only consumer product recalls, but also food, drug, and automotive recalls which have greater social impacts.

disclosure strategy affects investors' perceptions of the firm. She finds that a firm can mitigate the negative influence of criticism on Twitter by directly addressing the criticism and redirecting attention to positive information in the firm's disclosures. Together, these studies imply that an increase in two-way interactions on social media results in the provision of more comprehensive and complete information. As Miller and Skinner (2015) point out, the emergence of social media provides firms a new way of disseminating information, but the interactive features of social media bring new challenges for firms as they seek to manage the information environment.

2.4. Prior Literature on the Role of Twitter in Business Communication

As social media evolved, three platforms - Facebook, Twitter, and YouTube - either absorbed or replaced other platforms to become social media market leaders. Each platform has distinctive features that facilitate different types of communication among different groups of users. Twitter is ranked as the top platform by investor relations professionals (Jones, 2013). Twitter restricts tweets to 140-characters.[9] Twitter's short messages quickly grab recipients' attention, providing an ideal medium for sharing relevant information in a timely fashion, in contrast to the longer format and potentially reduced timeliness of research reports or articles (Bartov et al., 2017). Prior research consistently finds that social media has a significant influence on financial markets. For example, the mood of Twitter feeds can predict the movement of stock market indices (Zhang

[9] In my sample period, Twitter restricted tweets to 140-characters. Subsequent to my sample period, there have been several changes in the 140-character rule. On May 24, 2016, Twitter announced that a sender's handle, as well as media such as photos and videos, would not count against the 140-character limit. Previously, a photo was considered to be approximately 24 characters. In addition, attachments and links are no longer part of the character limit. On September 26, 2017, Twitter announced it was testing 280-character limit tweets. The 280-character limit went live for all users on November 7. Certain characters, including CJK, emoji and most Unicode symbols, count as two characters under the new limits.

et al., 2011; Bollen et al., 2011), and tweets are correlated with trading volume (Ruiz et al., 2012; Mao et al., 2012; Sprenger et al., 2014).

Blankespoor et al. (2013) find that the use of Twitter to “push” disclosures by embedding links to press releases is associated with reduced information asymmetry, as measured by lower abnormal bid-ask spreads and greater abnormal depth. Push dissemination is also positively associated with liquidity. Prokofieva (2014) also investigates the effect of dissemination of corporate disclosure via Twitter and finds that tweets posted by a firm decrease the information asymmetry proxied by the abnormal spread. She also finds that this negative association is stronger for firms with less business press or financial analyst coverage. Bhagwat and Burch (2016) provide additional evidence that Twitter allows companies to attract investors’ attention to firm disclosures. They find that tweets about earnings news increase the magnitude of announcement returns and that this effect is more significant for small, positive earnings surprises and when the firm is less visible as measured by firm size or analyst coverage. Together, these three studies provide evidence that Twitter allows companies to disseminate corporate announcements more effectively, attract investors' attention, and contribute to a decrease in information asymmetry.

Lee et al. (2015) document that by quickly informing customers and the public of consumer product recalls, social media disclosures help to minimize the spread of rumors and misinformation. However, they also find that social media can be a double-edged sword. Social media can exacerbate a crisis by spreading news to a wider audience, thereby helping the news to go viral. Their findings indicate that the benefits and costs of corporate social media usage vary with the level of control the firm has over its social media content. As social media disclosure becomes more prevalent, some top executives connect with investors directly, personally, and in real time through social media. Chen et al. (2018) find that personal tweets by CEOs and CFOs contain information that both improves stock market liquidity and exacerbates stock return volatility. They document that executive participation on social media grabs investor attention and enables retail investors to obtain value-relevant information to which they previously had no access.

Analyzing S&P 1500 firms' use of Twitter to disseminate quarterly earnings announcements, Jung, Naughton, Tahoun, and Wang (2018) find that social media outlets are more likely to be used to disseminate quarterly earnings news when the news is positive, suggesting that some firms are opportunistic in their use of social media. They also find that the market reaction is stronger for firms that follow a consistent social media disclosure policy. Crowley, Huang, and Lu (2018) also investigate firms' discretionary disclosure on Twitter. They find that firms' social media disclosure activities are more active around earnings announcements, accounting filings, and firm-specific news events. Unlike Jung et al. (2018), they find that firms are more likely to disseminate news on Twitter when it is significantly good or bad.[10] This finding suggests that firms are not opportunistic in their usage of social media. Although these two studies provide some contradictory findings, together they imply that managers exercise discretion regarding the level, timing, and format of disclosure on social media.

There are also a few papers that provide evidence on managers' use of discretion in the choice of social media disclosure. Using Newsweek's rankings of firms' environmental performance, Huang, Lu, and Su (2016) find that green firms are more likely to be early adopters of Twitter and tweet more frequently about their prosocial behavior. Yang and Liu (2017) find that

[10] There are several significant differences between Jung et al. (2018) and Crowley et al. (2018). First, the sample periods and sizes of the two studies are quite different. Second, Jung et al. (2018) adopt a dictionary approach, while Crowley et al. (2018) employ a machine learning approach to identify earnings announcement related tweets. Third, Jung et al. (2018) use earnings surprises to classify good or bad news as they focus solely on earnings announcements, while Crowley et al. (2018) use both RavenPack and CAR(-1,1) to classify good and bad news.

firms with earnings increases are more willing to use Twitter to disseminate earnings-related disclosure than are firms with earnings decreases.

Yang, Liu, and Zhou (2016) investigate the effect of corporate governance on the decision to disseminate earnings related disclosures on Twitter. They find that the dissemination of earnings news on Twitter is significantly associated with larger board size, greater gender diversity, and higher board effectiveness. Their findings provide evidence that corporate governance plays a significant role in decisions about social media disclosure. Baik, Cao, Choi, and Kim (2016) use geographic proximity as a measure of private information and find local Twitter users are more likely to tweet about firms with high information asymmetry, and their Twitter activity, in turn, increases the trading volume of local stocks. Together, these studies imply that as firms consistently disclose through the use of social media, investors become more informed and information asymmetry is reduced.

While prior studies contribute to our understanding of the effects of social media on financial markets, they generally focus on the response of investors. Although investors may be the primary audience for financial communication, firm disclosure through social media may also change the information environment for other stakeholders. Social media disclosure is often context specific, implying that information extraction and interpretation may require the acquisition and interpretation of objective, quantitative information or require context specific abilities such as industry or institutional knowledge (Blankespoor, 2018). Given the importance of financial analysts as information intermediaries, investigating the impact of social media disclosure on analyst behavior is important.

2.5. The Role of Financial Analysts as Information Intermediaries

Financial analysts are a primary information intermediary in capital markets (Womack, 1996; Jegadeesh, Kim, and Krische, 2004; Ivkovic and Jegadeesh, 2004; Asquith, Mikhail and Au, 2005). In response to the increased volume and complexity of firms' required disclosures, the role of financial analysts as information intermediaries is expanding (Lehavy et al., 2011; Lev and Gu, 2016). Analysts collect information from public and private sources and interpret complex communication using their expertise and industry knowledge (Jacob, Lys, and Neale, 1999; Ramnath, Rock, and Shane, 2008).

Prior research consistently finds that firm disclosure is an important determinant of analyst following and the properties of analyst forecasts. For example, Lang and Lundholm (1996) find that firms with more forthcoming direct investor relations communications have greater analyst following and more accurate analyst earnings forecasts, less dispersion among individual analyst forecasts, and less volatility in forecast revisions. Healy, Hutton, and Palepu (1999) show that firms whose disclosures provide greater information content have more accurate analyst earnings forecasts and less dispersion among individual analyst forecasts. Kross, Ro and Schroeder (1990) and Lys and Sohn (1990) find that analysts' earnings forecasts preceded by corporate accounting disclosures are more informative. Hope (2003) finds that across countries, the level of disclosure about accounting policies is inversely related to forecast errors and dispersion. Lehavy et al. (2011) find that less readable annual reports are associated with lower accuracy and greater dispersion of analyst forecasts.

Researchers also have investigated whether and how significant changes in the information environment resulting from Reg. FD impacted the behavior of analysts and the properties of their forecasts (Irani and Karamanou, 2003; Heflin, Subramanyam, and Zhang, 2003; Baily, Li, Mao, and Zhong, 2003; Agrawal, Chadha, and Chen, 2006; Mohanram and Sunder, 2006). Collectively, these studies find significant increases in analysts' earnings forecast errors and dispersion subsequent to Reg. FD.[11] These findings suggest that Reg. FD decreased the quantity and quality of publicly available information and also imply that the amount of information available to analysts is the key source of analysts' superior forecasting abilities.

Previous studies also find that analysts use soft information as well as hard information (Bradshaw, Wang, and Zhou, 2016; Huang and Mamo, 2016). Using firm specific print news coverage data, Bradshaw et al. (2016) find that the quantity of news coverage about a firm is positively associated with subsequent recommendation revisions, and that the tone of the news predicts the direction of the revisions. Huang and Mamo (2016) find that analysts' earnings forecast revisions are significantly influenced by the tone of news and that the relation between news and earnings forecast revisions is stronger when the news contains information regarding firm fundamentals. Together, these studies provide evidence that analysts are influenced by information provided by another information intermediary, the media.

Firms' business communication choices influence investors' information extraction costs (Bloomfield, 2002; Grossman and Stiglitz, 1980; Libby and Emett, 2014), and distinctive characteristics of social media can create fundamentally different information environments for information users. Social media disclosure provides more context specific information (Blankespoor, 2018). Considering that the intermediary role increases in importance with the

[11] Heflin et al. (2003) find neither forecast accuracy nor dispersion appear to change following Reg. FD, suggesting that Reg. FD did not restrict the information available to investors prior to earnings announcements.

difficulty of interpretation, context specific abilities such as the industry or institutional knowledge of financial analysts would be more valuable.

Analyst forecast revisions have information content (Griffin, 1976; Givoly and Lakonishok, 1979; 1980; Abdel-khalik and Ajinkya, 1982; Fried and Givoly, 1982; Imhoff and Lobo, 1984; Gleason and Lee, 2003; Ivkovic and Jegadeesh, 2004). They occur throughout the quarter and are the result of analysis and interpretation of new information. Forecast revisions are positively associated with the sign and magnitude of stock returns (Brown et al., 1985; Klein, 1990; Lys and Sohn, 1990; Beyer et al., 2010). Collectively, the studies on analyst forecasts and revisions suggest analysts play a valuable role as intermediaries (Guan, Lu, and Wong, 2012) and are sophisticated users of financial information (Chava, Kumar, and Warga, 2009). Brown, Call, Clement, and Sharp (2015) find that sell-side analysts are also valuable intermediaries, even for institutional investors.

Prior studies also have investigated a variety of factors that explain the magnitude of the market response to analyst forecast revisions. Clement and Tse (2003) find that the response varies with forecast accuracy. Barniv and Cao (2006) document that analyst characteristics and innovation explain investors' reactions to forecast revisions. Livnat and Zhang (2012) find that a significant percentage of analyst forecast revisions are issued promptly after a broad set of corporate public disclosures and that investors perceive these prompt revisions as more valuable than non-prompt revisions. Their findings indicate that investors value more highly analysts' ability to interpret public disclosures, especially less structured or non-financial disclosures, than analysts' information discovery.

2.6. Development of Hypotheses

As summarized above, research on the role of financial analysts as information intermediaries generally finds that investors react to the release of analysts' forecasts and forecast revisions. These findings imply investors view analysts as informed experts about companies' future operations. In addition, studies on firms' use of social media find social media disclosures are informative and are associated with reduced information asymmetry. Overall, both financial analysts and social media contribute to the efficient functioning of financial markets. However, it is unclear whether social media disclosures increase or decrease the need for financial analysts as information intermediaries, and whether the information on social media is correlated with the information used by analysts. Therefore, investigating the impact of social media disclosures on the intermediation role of financial analysts is necessary to fully understand the consequences of social media for companies and investors. Below, I discuss my predictions related to the relation between social media usage and analyst coverage, forecast accuracy, forecast dispersion, and the market reaction to forecast revisions.

The effect of social media disclosure on the demand for intermediation by financial analysts is ambiguous. Social media platforms undeniably reduce the costs a firm must bear to disseminate information and the costs information users must bear to gather information. This unique benefit of social media encourages firms to directly communicate with investors and thus would suggest a reduced demand for the intermediation role of financial analysts. This assumes that investors are able to process the information released on social media to develop earnings forecasts.

However, according to information overload theory, too much information can make it more difficult to understand an issue and to use information to make decisions. Although task performance initially improves as more information is available, Speier, Valacich, and Vessey (1999) find that as the amount of information begins to exceed the decision maker's processing capacity, performance eventually declines. The combination of more information and limited information processing capacity leads to information overload, which reduces decision making effectiveness. Information technology creates information overload because ideas are disseminated instantly and frequently (Evaristo, Adams, and Curley, 1995; Hiltz and Turoff, 1985). If social media disclosures produce excessive information, the disclosure could be treated as noise even when it contains information. Information overload can increase investor information analysis and interpretation costs, and, therefore, increase the need for an information intermediary. Moreover, disclosures must be interpreted and analyzed to have information content.

Social media disclosure has high flexibility in format, but low comparability in content compared to traditional SEC filings. Therefore, interpreting and judging the relevance and value of social media disclosure could be challenging to investors, thus suggesting an increased demand for financial analysts' intermediation. In addition, Bhushan (1989a; 1989b) and Lang and Lundholm (1993) argue that voluntary disclosure lowers the cost of information acquisition for analysts and hence increases the number of firms analysts follow. Overall, I expect greater use of social media to result in an increased demand for intermediation by financial analysts. As analysts are more likely to initiate coverage of firms for which investors have a high demand for intermediation, I predict a positive association between the use of social media and the number of analysts following a firm. Thus, my first hypothesis is as follows:

H1: The degree of corporate use of social media is positively associated with the number of analysts following the firm.

Another important question is whether social media disclosures undermine or reinforce the earnings forecasting abilities of financial analysts. Mosaic theory in finance refers to an analyst gleaning many different pieces of information to construct a sensible narrative and then deciding whether to recommend a trade (Pozen, 2005). This involves collecting public, non-public, material, and immaterial information about a company in order to determine the underlying value of the company's securities (Caccese, 1997; Davidowitz, 2014). Following Mosaic theory, skilled analysts with industry knowledge will interpret, analyze, and combine immaterial information with material information. Therefore, even information that is immaterial on its own contributes to reaching a conclusion. Given that even immaterial information is useful to financial analysts, Mosaic theory suggests that disclosure through social media is a valuable additional information source. Therefore, expanded disclosure through social media potentially enables financial analysts to create valuable new information, such as superior forecasts and reinforces the intermediation role. As ambiguity and uncertainty among analysts concerning the future performance of the company decreases, the level of disagreement among analysts' forecasts also decreases. Thus, my second and third hypotheses are as follow:

H2: The degree of corporate use of social media is positively associated with analysts' forecast accuracy.

H3: The degree of corporate use of social media is negatively associated with dispersion of analysts' forecasts.

Market participants value analysts' forecasts because they believe analysts provide new information about the industry, firm, and macro economy, as well as informative interpretations of financial statements and public disclosures (Beaver, Cornell, Landsman, and Stubben, 2008; Clement, Hales, and Xue, 2011; Baginski, Hassell, and Wieland, 2011). Livnat and Zhang (2012) find that investors especially appreciate analysts' interpretation of less structured or non-financial disclosures. Social media disclosures are unstructured, implying that when a firm uses social media, analyst forecast revisions will be particularly useful to investors because there is more information to interpret. I also expect analysts to work harder because there is more information to interpret. Thus, my fourth hypothesis is:

H4: The degree of corporate use of social media is positively associated with the market response to analyst forecasts revisions.

3. DATA AND RESEARCH DESIGN

Chapter 3 discusses sample selection and research design. I begin with a discussion of the sample used in the analyses. I then discuss the social media disclosures used to test my hypotheses, followed by the measures of analyst coverage and properties of analyst forecasts that are my dependent variables. Then, I present the empirical model used to test H1, which predicts a positive association between the degree of corporate use of social media and the number of analysts following the firm. Next, I present the empirical model used to test H2 (H3), which predicts a positive (negative) association between the corporate use of social media and analysts' forecast accuracy (dispersion of analysts' forecasts). Lastly, I present the empirical model used to test H4, which predicts a positive association between the degree of corporate use of social media and the market response to analyst forecast revisions.

3.1. Data

To investigate the effect of social media disclosure on analyst following, the properties of analyst earnings forecasts, and the market reaction to analyst forecast revisions, I analyze the social media activity of S&P 500 firms from the first calendar quarter of 2012 through the fourth quarter of 2014, a period that includes the April 2, 2013, SEC rule permitting the initial disclosure of material nonpublic information on social media. The initial sample consists of firm-quarters with data available on Compustat, Thomson Reuters Financial, I/B/E/S, EDGAR, and Twitter. I extract analyst forecast and management forecast data from I/B/E/S, financial data from Compustat Quarterly and Segment files, and institutional ownership from Thomson Reuters Financial. I obtain complete historical Twitter data from CrimsonHexagon, one of the official resellers of Twitter data. I winsorize all independent and dependent variables at the top and bottom one percent. As shown in Table 1, excluding observations without information needed to estimate the control variables reduces my initial sample from 6,000 to 4,974 firm-quarter observations.

3.2. Measures of Social Media Disclosure

Social media research in accounting is still evolving, and measures of social media activity are not yet well established. Previous studies count the number of tweets during a specific short window period around news events such as earnings announcement dates and product recall announcements (Lee et al., 2015; Blankespoor et al., 2013). In contrast, this study distinguishes itself from most studies that focus on specific events by focusing on the level of Twitter disclosure activity of firms and interactions among stakeholders and potential investors aggregated at the firm level.

I create three measures that capture disclosure about a firm on Twitter – the number of tweets on financial topics by the firm, the number of tweets on non-financial topics by the firm, and the number of tweets about the firm by the public. To measure the number of financial tweets released by the firm, I count the number of tweets that originate from the Twitter account linked to the firm's Website and contain financial keywords such as 'earnings', 'EPS', and 'revenue'. The list of financial keywords is developed from Loughran & McDonald's (2014) Master Dictionary, which I augmented by an analysis of the frequency with which various words appear in SEC 10-K filings. I first restrict the augmented word list to those words used more than 100,000 times in 10-Ks filed from 1994 to 2014. From that subset, four individuals with work experience as financial accountants individually identified the words they considered to be related to the firm's financial performance. Any words determined to be financial-related by at least two of the four individuals were retained in the dictionary. Second, I measure the number of nonfinancial tweets by counting the number of tweets from the firm's official Twitter account that do not contain financial keywords. Finally, to measure the amount of financial information shared by social media users other than the firm, I count the number of tweets that do not originate from the firm's twitter account and contain the firm's Cashtag.

3.3. Measures of Analyst Coverage and Properties of Forecasts

Analyst coverage is measured as the number of analysts who comprise the most recent I/B/E/S consensus quarterly earnings forecast prior to the quarterly fiscal period ending date. Following prior literature (e.g., Schipper, 1991; Brown, 1993), I calculate the forecast error for firm i in quarter t as the absolute value of forecast EPS less actual EPS, scaled by actual EPS, where forecast EPS is based on the last consensus quarterly earnings forecast before the financial period ending date of the I/B/E/S Summary data:

$$Forecast\ Error_{i,t} = \left| \frac{Forecasted\ EPS_{i,t} - Actual\ EPS_{i,t}}{Actual\ EPS_{i,t}} \right|$$

Analyst forecast dispersion is computed as the standard deviation from the last consensus quarterly earnings forecast before the financial period ending date on the I/B/E/S Summary data file.

3.4. Research Design

3.4.1. Analyst Following Model

To examine the effect of social media disclosure on the intermediary role of financial analysts, I estimate the following regression model:[12]

$$\begin{aligned} Following_{it} = {} & \alpha_0 + \alpha_1 Financial\_Tweets_{it} + \alpha_2 Non\text{-}financial\_Tweets_{it} + \\ & \alpha_3 Crowd\_Tweets_{it} + \alpha_4 News_{it} + \alpha_5 Size_{it} + \alpha_6 BtoM_{it} + \alpha_7 Loss_{it} + \alpha_8 ROA_{it} \\ & + \alpha_9 Leverage_{it} + \alpha_{10} Intangible\_Asset_{it} + \alpha_{11} R\&D_{it} + \alpha_{12} Bus\_Seg_{it} + \end{aligned}$$

[12] The twelve industry classifications are defined in appendix B. Time fixed effects are controlled using twelve indicator variables, one for each of the twelve calendar quarters in my sample period.

$\alpha_{13}Geo\_Seg_{it}$ + $\alpha_{14}Institutional_{it}$ + $\alpha_{15}8\text{-}K_{it}$ + $\alpha_{16}Management\_Qtr_{it}$ +

Industry Fixed Effects +*Time Fixed Effects* + ε (1)

Equation (1) is estimated using a negative binomial count-data model with industry and time indicators.[13] Similar to prior research (O'Brien and Bhushnan, 1990; Brennan and Subrahmanyam, 1995; Lehavy et al., 2011), I define analyst following, *Following*, as the number of analysts that comprise the last consensus quarterly earnings forecast before the financial period ending date on the I/B/E/S Summary data file for firm i in quarter t. Following Bhushan (1989) and Lehavy et al. (2011), I interpret this measure as a proxy for the collective effort of the financial analyst community in the analysis of an individual firm.

The variables of interest, *Financial_Tweets*, *Non-financial_Tweets*, and *Crowd_Tweets*, capture the amount of information released on social media by firm i in quarter t and information shared by others about the firm over the quarter. My first hypothesis predicts that the degree of social media usage by the firm is associated with the demand and/or supply of information from financial analysts. Support for H1 implies that α_1, the coefficient on *Financial_Tweets*, will be positive. The degree of information shared by the crowd is a good proxy for the degree of public attention and public demand for information about a firm. Therefore, I also expect *Crowd_Tweets* to be positively associated with *Following,* i.e., α_3 is expected to be positive.

[13] Rock, Sedo, and Willenborg (2001) show that when analyzing count data such as analyst coverage (i.e. nonnegative integer data), the negative binomial model is more appropriate than the OLS or Poisson models and better captures the true underlying data generating process. It also addresses the econometric issues associated with truncation (zero value) and over-dispersion (lower standard error) in the data.

3.4.1.1. Control Variables for Analyst Following Model

In addition to the social media variables of interest, I include control variables identified by the prior literature as explaining analyst following and the properties of analyst forecasts. First, I control for the volume of fact-based articles containing financial news provided by formal news organizations each quarter to ensure my variables of interest are not just capturing the overall volume of available information.[14] By controlling for the volume of financial information released in other traditional media outlets, I can investigate whether my variables of interest are associated with the demand and/or supply of information from financial analysts. If a greater volume of coverage by traditional media also results in an increased demand for intermediation by financial analysts, analysts are more likely to initiate coverage of firms that have a high demand for intermediation. Therefore, I predict a positive association between the volume of fact-based articles containing financial news provided by formal news organizations and the number of analysts following a firm.

Additional control variables include firm size, book-to-market ratio, return on assets, leverage, and an indicator variable for losses.[15] Previous studies document that firm size is the most important explanator of analyst following, with larger firms having greater following (Bhushan, 1989; O'Brien and Bhushan, 1990; Brennan and Hughes, 1991; Lang and Lundholm, 1996; Barth, Kasznik, and McNichols, 2001). To control for size, I include the natural log of market value. Following prior work, I include book-to-market, an inverse proxy for growth (Smith

[14] I use the 'News' content source option from CrimsonHexagon, which provides full access to all available "Fact-based articles by formal news organizations, such as CNN, New York Times, Wall Street Journal, etc." using web searches. I retain each article containing an official name of a specific company and at least one of the words from the financial key words dictionary developed for financial tweets.

[15] Size, book-to-market ratio, leverage, return on assets, and the loss indicator variable are measured at the end of the quarter t.

and Watts, 1992; Barth et al., 2001; Lehavy et al., 2011). To control for firm performance, I include return on assets, a loss indicator variable, and financial leverage.

I also include controls for the level of business complexity and the degree of information asymmetry between a firm and its market participants. Barth et al. (2001) find analysts have greater incentives to follow firms with larger intangible assets, which are more difficult for investors to value. They find analyst coverage is significantly greater for firms with larger R&D expenses relative to their industry peers. I include both intangible assets scaled by total assets and the dollar value of research and development expenditures as controls. To control for the effect of business complexity, I include the number of reported business and geographic segments as of the ending date of the previous fiscal year (Bradshaw, 2009; Lehavy et al., 2011). Prior research also documents that analyst coverage is associated with the number of institutional investors (Bhushan, 1989; O'Brien and Bhushan, 1990; Brennan and Subrahmanyam, 1995; and Frankel, Kothari, and Weber, 2006). To control for the level of institutional holdings, I include the percentage of institutional ownership as of the quarter ending date (Ljungqvist, Marston, Starks, Wei, and Yan 2007; Bae, Stulz, and Tan, 2008). I include the number of Form 8-K filings issued over the quarter to control for the amount of information distributed through SEC filings, which I expect to be positively associated with the number of analysts following a firm. Finally, following Lehavy et al. (2011), I include the number of management forecasts issued each quarter by the firm as a proxy for the firm's discretionary disclosure (Nagar, Nanda, and Wysocki, 2003; Cotter, Tuna, and Wysocki, 2006). On one hand, management forecasts may increase analyst following because there is more information to interpret and an increased demand for the intermediary role of financial analysts. On the other hand, earnings forecasts provided by management may preempt or substitute for information processing by financial analysts because there is already a benchmark of the firm's future performance. Therefore, the impact of management forecasts on analyst following is an empirical question.

3.4.2. Forecast Properties Model

To examine the effect of social media disclosures on the properties of analyst earnings forecasts (H2), I estimate the following OLS regression model:

$$
\begin{aligned}
Forecast\_Properties_{it} = {} & \beta_0 + \beta_1 Financial\_Tweets_{it} + \beta_2 Non\text{-}financial\_Tweets_{it} + \\
& \beta_3 Crowd\_Tweets_{it} + \beta_4 News_{it} + \beta_5 Following_{it} + \beta_6 Horizon_{it} + \beta_7 Size_{it} \\
& + \beta_8 BtoM_{it} + \beta_9 Loss_{it} + \beta_{10} ROA_{it} + \beta_{11} Leverage_{it} + \\
& \beta_{12} Intangible\_Asset_{it} + \beta_{13} R\&D_{it} + \beta_{14} Bus\_Seg_{it} + \beta_{15} Geo\_Seg_{it} + \\
& \beta_{16} Institutional_{it} + \beta_{17} 8\text{-}K_{it} + + \beta_{18} Management\_Qtr_{it} + Industry\ Fixed \\
& Effects + Time\ Fixed\ Effects + \varepsilon \qquad (2)
\end{aligned}
$$

Model (2) is estimated using ordinary least-squares (OLS) regression with industry and time indicators to control for industry and time fixed effects.[16] This model is estimated separately for *Forecast_Error* and *Forecast_Dispersion*.

3.4.2.1. Control Variables for Forecast Properties Model

Bagnoli, Levine, and Watts (2005) find that news released by a firm through traditional media outlets has a significant influence on analysts' forecasting activity. In addition, Huang and Mamo (2016) find that company information disseminated via news media outlets influences analysts' earnings revisions. Therefore, I include a control variable for the natural log of the volume of articles containing financial news provided by traditional news organizations over the

[16] Industry fixed effects are controlled using 12 indicator variables that each represent one industry division. Classification of industry divisions is discussed in appendix B. Time fixed effects are controlled using quarterly time indicator variables 1 through 12 to capture the twelve quarters.

quarter to ensure my variables of interest are not proxying for the overall volume of information available. I also include analyst following, measured as the number of analysts who compromise the most recent I/B/E/S consensus quarterly earnings forecast prior to the quarterly financial period ending date to proxy for the time, effort, and resources analysts devote to gathering and analyzing information about the firm. Analyst coverage is expected to be negatively related to the level of information asymmetry and, therefore, *Forecast_Error* and *Forecast_Dispersion*. O'Brien (1988) finds that recent forecasts are more accurate. *Horizon* is included in the model to control for the amount of time elapsed between the forecast date and the related earnings announcement date. Prior studies find that larger firms have richer information environments and potentially smaller *Forecast_Error* and *Forecast_Dispersion* (Bhushan, 1989; O'Brien and Bhushan, 1990; Brennan and Hughes, 1991; Lang and Lundholm, 1996; Barth et al., 2001). I include *Size* as of the ending date of the quarter to control for the impact of the general information environment. I include *ROA* because prior research also concludes that more profitable firms have higher analyst following and, therefore, lower information asymmetry. I include a control for leverage as of the end of each quarter because Thomas (2002) presents evidence that highly leveraged firms have less accurate and more highly dispersed forecasts. I also include *Loss*, an indicator variable equal to 1 if the firm reported a quarterly loss because firms suffering losses may have a different information environment due to stakeholder dynamics. The valuation of growth opportunities is more difficult than the valuation of assets in place, and book to market, an inverse proxy for growth opportunities is expected to be positively associated with *Forecast_Error* and *Forecast Dispersion* (Smith and Watts, 1992). [17]

[17] Book-to-market is calculated as book value of equity divided by market value of equity as of the end of quarter t.

I also include controls for the level of business complexity and the degree of information asymmetry between a firm and its market participants. Previous studies suggest that as forecast complexity increases, analyst forecast accuracy deteriorates (Haw, Jung, and Ruland, 1994; Duru and Reeb, 2002; Lehavy et al., 2011). To control for forecast complexity, my model includes intangible assets scaled by total assets and the dollar value of research and development expenditures. Also, to control for the effect of business complexity, I include the number of business and geographic segments (Bradshaw et al., 2009, Lehavy et al., 2011). Previous studies also find that institutional ownership is associated with higher analyst forecast accuracy and lower dispersion because firms with high levels of institutional holdings tend to have a richer information environment (Brennan and Subrahmanyam, 1995; Frankel et al., 2006). Therefore, to control for the effect of institutional ownership, I include a control for the level of institutional holdings (Ljungqvist et al., 2007; Bae et al., 2008; Lehavy et al., 2011). I include the number of Form 8-K filings issued over the quarter to control for the amount of information released through SEC filings. Finally, following Lehavy et al. (2011), I include the number of management forecasts issued over the quarter by the firm to control for the amount of information conveyed through other forms of voluntary disclosure.

3.4.3. Market Reaction to Analyst Forecast Revisions Model

To examine the impact of social media disclosures on the market reaction to analysts' forecast revisions (H4), I estimate the following OLS regression model:

$$\begin{aligned} CAR(0,1)_{jit} = {} & \gamma_0 + \gamma_1\, Mean\_AFRevise_{it} + \gamma_2\, Mean\_AFRevise_{it} * \\ & Log\_Financial\_Tweet_{it} + \gamma_3\, Log\_Financial\_Tweet_{it} + \\ & \gamma_4\, News_{it} + \gamma_5 Size_{it-1} + \gamma_6 BtoM_{it} + \gamma_7 Leverage_{it} + \gamma_8 Total\_Revise_{it} + \\ & \gamma_9 8\text{-}K_{it} + \gamma_{10} Management\_Ind_{it} + \varepsilon \end{aligned} \tag{3}$$

Consistent with prior research (Green, Jame, Markov, and Subasi, 2014; Huang, Zang, and Zheng, 2014), the dependent variable, *CAR(0,1)*, is abnormal returns cumulated over the two-day window beginning on the date that the forecast revision is released. I use market-adjusted returns. The daily abnormal returns are calculated as the firm-specific return less the CRSP value-weighted return.

I compute the average analyst forecast revision, $Mean\_AFRevise_{ijt}$, as follows. For each individual sell-side analyst, the analyst forecast revision by analyst j for firm i at time t is measured as ($AF_{i,j,t}$ - $AF_{i,j,t-1}$), where $AF_{i,j,t-1}$ is the most recent earnings forecast by analyst *i* for firm *j* prior to $AF_{i,j,t}$, based on the I/B/E/S detail data. Both analyst forecasts and stock price are adjusted for stock splits, consistent with Payne and Thomas (2003). Each revision is then scaled by one-month prior stock price. If there are multiple individual analyst forecast revisions for firm *j* on day *t*, I use the average analyst forecast revision on day *t*. Thus, my variable measures the average news about the firm's expected earnings on day t.

Prior research, for example Loh and Stulz (2018), exclude days when multiple analysts issue forecasts. However, they note this may result in bias to the extent revisions are clustered on days with news releases. Rather than eliminating these forecast revisions, I use the average analyst forecast revisions for firm *j* on day *t*. I also winsorize the top and bottom 1% of each independent and dependent variable to mitigate outlier effects. To capture social media activity between analyst forecasts, *Log_Financial_Tweet* is calculated as the log of one plus the sum of daily firm financial-related tweets between the prior analyst forecast and the current analyst forecast.[18]

In Eq. (3), the main variable of interest is the interaction term, *AFRevise * Log_Financial_Tweet*. This variable captures the impact of social media disclosure on the market

[18] Because the length of time between the prior analyst forecast and the current analyst forecast is not fixed, the sum of daily firm financial-related tweets over the revision periods is highly skewed. Considering this, I use logged values of the variable instead of the raw values.

response to a forecast revision. A positive and significant coefficient, γ_2 implies that the higher the level of social media activity, the greater the association between analysts' forecast revisions and the market response to the revision. In addition, the higher the level of forecast revision, the greater the association between social media activity and market response.

3.4.3.1. Control Variables for Market Reaction to Analyst Forecast Revisions Model

Nicholas and Wieland (2009) document that popular press news influences the market reaction to analysts' forecast revisions. To control for the impact of information via traditional media and press releases, I include a control variable, *News*, equal to the log of the volume of financial news about the firm released by formal news organizations between the previous and the current analyst forecast revision dates. I also include various controls identified by prior literature as potentially affecting the sensitivity of price to analyst forecast revisions. To control for the influence of analyst coverage, I include the number of analysts who issue a revision on the forecast revision date, *Total_Revise*. Brennan, Jegadeesh, and Swaminathan (1993) find that stocks with greater analyst coverage react faster to market-wide common information. Following Gleason and Lee (2003) and Bonner, Hugon, and Walther (2007), I control for firm characteristics such as size (*SIZE*), book-to-market ratio (*BtoM)*, and leverage (*Leverage*). [19] I also control for the total number of Form 8-Ks filed by each firm between the prior analyst forecast and the current analyst forecast revision. Finally, following Lehavy et al. (2011), to control for other voluntary disclosures by the firm, I include an indicator variable equal to one if there is at least one management forecast of EPS issued between the previous and current forecast revision (*Management_Ind*).

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[19] Size is measured as of quarter t-1, where quarter t is the quarter in which the analyst forecast revision is released. Book-to-Market and leverage are measured as of the beginning of the quarter in which the analyst forecast revision is released.

4. EMPIRICAL RESULTS

In Chapter 4, I provide descriptive statistics for the complete sample and a profile analysis that compares the characteristics of firms whose financial tweet volume in the first quarter of 2014 is in the top quartile of the sample with the characteristics of firms in the bottom quartile. I then present the main empirical results of multivariate tests of H1 through H4.

4.1. Descriptive Statistics

Descriptive statistics for the key variables used in this study are reported in Table 2. Of the S&P 500 firms, 65 firms do not have official Twitter accounts linked to their official company Websites. I remove these 65 firms from my sample, leaving 435 unique firms and 4,974 quarterly observations. The mean and standard deviation of financial tweets by the firm per firm-quarter are 143 and 35, respectively. The minimum and maximum values per firm-quarter are 92 and 211, respectively, implying that there is significant variation across firms in the amount of financial information shared via social media. The mean and standard deviation of non-financial tweets by the firm per firm-quarter are 267 and 79, respectively. Minimum and maximum values of non-financial tweets per firm-quarter are 135 and 392. The mean and standard deviation of tweets about the firm that contain a Cashtag (*Crowd_Tweets*) is 5,246 and 2,734 per firm-quarter, respectively.[20]

There is also significant variation across firms in the amount of financial information shared via other sources such as traditional media, SEC filings, and discretionary disclosure. The mean and standard deviation of the logged values of financial news by traditional media per firm-quarter are 4.7 and 2.2, respectively which are 110 and 9 in raw values. The mean and standard deviation of the number of Form 8-K filings per firm-quarter is 3.6 and 2.4, respectively. On average, there are 1.25 management forecasts per firm-quarter, and the standard deviation is 0.58.

[20] Table 2 presents the values of Crowd_Tweets scaled by 100.

Descriptive statistics also include general information on the sample firms' analyst forecasts.[21] The average analyst following is 18.32 analysts, and the range is from 3 to 38 analysts. The mean values of forecast error and dispersion are 13.7% and 0.05, respectively. The average forecast horizon is 12.84 days, with a standard deviation of 12.48 days.

Finally, in terms of firm characteristics, the mean and standard deviation of the logged values of firm size are 4.2 and 0.43, which indicates firm size does not vary significantly, reflective of the fact that sample firms are in the S&P 500. The variable, *BtoM*, has a mean of 0.47 and standard deviation of 0.40. On average, only 5.8% of firms reported a loss during the sample period, reflective of the fact that sample firms are in the S&P 500. The average and standard deviation of *ROA* per firm-quarter for sample period are 0.02 and 0.02, respectively. The mean and standard deviation of the leverage ratio are 0.62 and 0.2. The mean value of *Intangible Asset* and *R&D* are 0.72 and 107.07 million, respectively and indicate that sample firms have a high percentage of intangible assets compared to total assets and that they spend a significant amount on research and development. The average number of reported business segments and geographic segments of sample firms are 3.3 and 1.2. On average, 71.5% of a firm's shares are held by institutions as of the quarter ending date of the sample period.

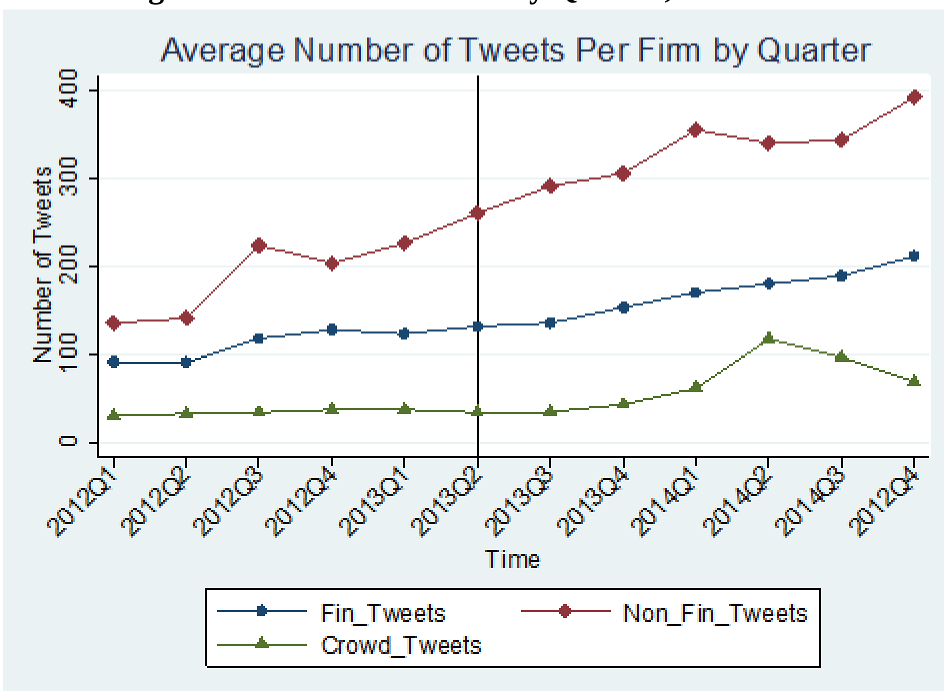
4.2. Profile Analysis

In Table 3, I compare the firm characteristics of the quartile of firms that released the largest number of financial tweets in the first quarter of 2014 to the characteristics of the quartile of firms with the lowest number of financial tweets in the first quarter of 2014. I select 2014 because Figure 1 shows that the average number of tweets per firm and the average number of

[21] The mean value of analyst following is greater and the mean values of forecasts error and dispersion are similar to or smaller than values of previous studies, e.g., Lang and Lundholm (1996) and Lehavy et al. (2011), reflective of the fact that my sample firms are in the S&P 500.

Cashtag tweets by the public are generally increasing throughout the sample period. Thus, 2014 reflects the most mature stage of social media usage. The results of the t-test (Wilcoxon test) show that the mean (median) values of the volume of nonfinancial information released on Twitter, the volume of tweets about a firm by the public, the volume of financial news about a firm covered by traditional media, analyst following, size, and leverage are significantly larger for the firms in the top quartile. On the other hand, earnings forecast dispersion, book-to-market ratio, business segments, geographic segments, and the degree of institutional ownership are significantly smaller.

Figure 1. Number of Tweets by Quarter, 2012-2014 [a]



[a] Crowd_Tweets are in 100s.

4.3. Correlation Analysis

Table 4 reports pairwise correlations among the variables. The Twitter variables are highly correlated with each other. The correlation between *Financial_Tweets* and *Non-financial_Tweets* is 0.74, implying that social media usage is a firm-level choice that is reflected in the volume of both financial and nonfinancial tweets.[22] *News* is positively correlated with all three Twitter variables. Each of the three Twitter variables is positively correlated with *Following*. *Error* and *Dispersion* are negatively correlated with both *Financial_Tweets* and *Non-financial_Tweets*, implying that forecast errors and dispersion are smaller as the volume of information released through Twitter increases. In contrast, the *Crowd_Tweets* variable is significantly and positively correlated with *Error* and *Dispersion*. One interpretation is that there is a positive correlation between the heterogeneity of analyst and investor beliefs, with the latter reflected in a higher volume of crowd tweets.

4.4. Regression Results

4.4.1. Analyst Following

Table 5 presents the multivariate regression results from the estimation of equation (1), which tests the H1 prediction that analyst following is positively associated with social media usage.[23] The coefficient on *Financial_Tweets* is significant and positive ($p<0.05$), indicating a positive association between social media usage and analyst following. The coefficient on *Non-financial_Tweets* is significant and negative ($p<0.01$), after controlling for *Financial_Tweets*. Given the high correlation between these two variables, I re-estimate the model without *Financial_Tweets* (untabulated) and find that the coefficient on *Non-financial_Tweets* is positive and significant. This suggests that analysts find both financial and nonfinancial tweets to increase demand for information. The coefficient on *Crowd_Tweets* is insignificant. One possible interpretation is that the crowd may not provide additional information.

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[22] Variance inflation factors (VIFs) for all variables in all models are no larger than 3, indicating multicollinearity is not a concern.

[23] The multivariate regression for the analysis of analyst following adopts the negative binomial model following Rock, Sedo, and Willenborg (2001) to address the econometric issues associated with truncation (zero value) and over-dispersion (lower standard error) in the data. The pseudo R^2 from the negative binomial model is not comparable to the adjusted R^2. Therefore, I do not compare the explanatory power of my model to the adjusted R^2 of previous studies on the variability of analyst following around its mean.

Similar to prior research (Bhushan, 1989; O'Brien and Bhushan, 1990; Brennan and Hughes, 1991; Lang and Lundholm, 1996; Barth et al., 2001; Lehavy et al., 2011), I find *Size* is significantly and positively ($p<0.01$) associated with *Following*. Consistent with Barth et al. (2001), I document analyst following is smaller for firms with higher growth ($p<0.01$). Consistent with previous work (Bhushan, 1989; O'Brien and Bhushan, 1990; Brennan and Subrahmanyam, 1995; and Frankel et al., 2006), I find that institutional ownership is positively ($p<0.01$) associated with analyst following. As predicted, I also find that the volume of fact-based articles containing financial news provided by formal news organizations is positively and significantly ($p<0.01$) associated with analyst following, while the impact of the volume of management forecasts on analyst following is insignificant.

4.4.2. Forecast Error

Table 6 presents the multivariate regression results of estimating equation (2) with forecast error as the forecast property of interest.[24] Consistent with H2, I find that the coefficient on *Financial_Tweets* is significant and negative ($p<0.10$). This supports the hypothesis that social media usage is positively associated with analyst forecast accuracy. This finding provides evidence that financial information delivered via social media provides incremental information to analysts in addition to that provided by traditional media. The coefficient on *Non-financial_Tweets* is not significant. The coefficient on *Crowd_Tweets* is significant and positive ($p<0.01$). There are several possible interpretations. First, on average, the crowd may provide misleading, meaningless information. Second, processing of divergent information involves more screening, evaluating, and interpreting (Schick, Gordo, and Haka, 1990) and these tweets may contribute to information

[24] The multivariate regression model for the analysis of forecast error has an adjusted R^2 of 0.216, which indicates that my model explains about 22% of the variability of analyst forecast error around its mean. Lehavy et al. (2011), Dhaliwal, Radhakrishnan, Tsang, and Yang (2012), and Lang and Lundholm (1993) report adjusted R^2 of 0.05, 0.12, and 0.38, respectively. Compared to the previous studies, my model has a decent level of explanatory power.

overload and a decline in forecasting performance (Agnew and Szykman, 2005). Alternatively, the volume of crowd tweets reflects general market uncertainty about the firm's future prospects.

As expected, I also find analyst coverage is negatively ($p<0.05$) associated with *Forecast_Error*. Similar to prior research (Bhushan, 1989; O'Brien and Bhushan, 1990; Brennan and Hughes, 1991; Lang and Lundholm, 1996; Barth et al., 2001; Lehavy et al., 2011), I find *Size* is significantly and negatively ($p<0.05$) associated with *Forecast_Error*. This implies that larger firms have richer information environments. Firms with greater R&D expenses have lower forecast accuracy ($p<0.01$). This finding is consistent with previous research documenting that analyst forecast accuracy deteriorates as forecast complexity increases (Haw et al., 1994; Duru and Reeb, 2002; Lehavy et al., 2011). While *News* is positively and significantly ($p<0.01$) associated with analyst following, I find that it does not have a significant impact on forecast accuracy. This finding may indicate that the amount of information available about a specific firm increases the demand for analysts as information intermediaries, but that there is significant redundancy among articles provided by traditional media and that analysts do not view the redundancy to be informative. *Management Forecasts* is not significantly associated with analyst following. However, it is negatively and significantly ($p<0.05$) associated with analyst forecast error. This finding implies that financial analysts view management forecasts as value relevant voluntary disclosures.

4.4.3. Forecast Dispersion[25]

Table 7 presents multivariate regression results on forecast dispersion. Inconsistent with H3, I do not find a significant negative association between firm social media disclosure and forecast dispersion. The combined findings indicate that social media usage is associated with

[25] The multivariate regression model for the analysis of forecast dispersion has an adjusted R^2 value of 0.235, which indicates that my model explains about 24% of the variability of analyst forecasts dispersion around its mean. Lehavy et al. (2011), and Lang and Lundholm (1993) report adjusted R^2 of 0.20, and 0.42, respectively.

improved forecast accuracy, but the additional information does not lead to a decrease in the heterogeneity of analyst beliefs.

As predicted, I find *Following* is negatively and significantly ($p<0.01$) associated with *Forecast_Dispersion*. This finding is consistent with the prediction that analyst coverage is negatively related to the level of information asymmetry. *News* is not significantly associated with forecast dispersion. This could be due to the redundancy of information or diversified information from media not reducing uncertainty in the prediction of future performance. I do not find significant associations between other control variables representing forecast complexity (i.e. *R&D, Business_Seg, Geo_Seg*) and *Forecast_Dispersion*.

4.4.4. Market Reaction to Forecast Revisions[26]

Table 8 reports descriptive statistics for the key variables used in the analysis of the market reaction to forecast revisions. There are 25,835 revisions with complete data. The average number of revisions per firm quarter is 4.95. The mean and standard deviation of 2-day cumulative abnormal returns, (*CAR(0,1)*), in response to average forecast revisions are 0.005% and 2.5%, respectively. This indicates that, on average, there is a positive market response to analyst forecast revisions. The minimum and maximum values of *CAR (0,1)* are -36.1% and 29.7%, respectively, implying that there is significant variation across firms in the direction and amount of financial information captured in analyst forecast revisions. The mean and standard deviation of *Mean_AFRevise* are -0.001 and 0.011, respectively. The minimum and maximum values of *News* are 0 and 3.019, respectively which are 0 and 21 in raw values, implying that the amount of

[26] The multivariate regression model for the analysis of the market response to analyst forecast revisions has an adjusted R^2 of 0.008, which indicates that my model explains about 0.8% of the variability in abnormal two-day abnormal returns in response to the forecast revision release. In contrast, the adjusted R^2 in Green et al. (2014) is 0.23. However, it is difficult to make a direct comparison between the explanatory power of the two models because Green et al. (2014) classify forecast revisions into only two categories (upward revisions and downward revisions), while my study uses the mean analyst forecast revision on day t scaled by stock price at the end of the prior month.

traditional media coverage of a firm's financial news in between analyst forecast revisions varies significantly. The mean values of *Size*, *BtoM*, *Leverage* are 9.878, 0.468, and 0.600, respectively. On average, 1.83 analysts issue revisions on the forecast revision date. The average number of Form 8-Ks filed over the revision period is 0.263, and about 10% of sample firms issue at least one management forecast between the previous and current forecast revision dates.

Table 9 reports multivariate regression results for the market reaction tests. Consistent with prior research, I expect a significant market response to analysts' forecast revisions. To examine the effect of analyst forecast revisions on stock price discovery in the social media era, I first run the model without the social media and social media interaction variables, *Log_Financial_Tweet* and *AFRevise*Log_Financial_Tweet*. I find a significant market reaction to analyst forecast revisions, indicating that analysts remain an important information intermediary in the social media disclosure era. In the second model, I include *Log_Financial_Tweet*, but not *AFRevise*Log_Financial_Tweet*. I again find that analyst forecast revisions have a significant association with two-day returns.

The primary test of my fourth hypothesis is the third model, which includes the mean forecast revision, the financial tweets variable, and the interaction term. Both the mean revision ($p<0.05$) and the interaction term are positive and significant ($p<0.10$). The significance of the interaction term using the two continuous variables implies that the higher the level of social media activity, the greater the association between analyst forecast revisions and the market responses to the revisions. In addition, the larger the forecast revision, the greater is the association between social media activity and the market response. The coefficient on the number of tweets is again insignificant. These findings suggest social media disclosures complement rather than substitute for the intermediary role of financial analysts, consistent with mosaic theory (Pozen, 2005).

In addition to the variables of interest, I find *News* ($p<0.05$) and *Size* ($p<0.01$) are significantly positively and negatively associated with the market response, respectively. The coefficients on *News* are consistently positive and significant for all three specifications. This finding is in line with the significant and positive association with *News* and analyst following. Although *News* is not significant in either the *Forecast_Error* or *Forecast_Dispersion* models, these findings imply that investors still value information available from financial news articles by traditional news providers. Negative and significant coefficients on *Size* imply that bigger firms' stock prices are less responsive to news releases because they have richer information environments, implying that more of the information in the release has already been impounded in price.

5. SUPPLEMENTAL ANALYSES

In Chapter 5, I perform several additional analyses to validate the main results and to provide enhanced perspectives about the main findings reported in Chapter 4. I begin by estimating the analyst following, analyst forecast error, and analyst forecast dispersion models for subsamples of firms in consumer-oriented versus non-consumer-oriented industries to further rule out concerns that the results of my main analyses are influenced by particular industries. I also examine the impact of social media on the market response to analyst forecast revisions using a three-day Cumulative Abnormal Returns (CARs) window to show that the findings of my main analyses are robust to specification of the length of the event window. I conclude by examining the impact of social media on the market response to analyst forecast revisions for the subsamples of firms that do versus do not issue management forecasts of EPS between the previous and current forecast revisions.

5.1. Analysis of Analyst Following, Analyst Forecast Errors, and Analyst Forecast Dispersion for Subsamples of Companies in Consumer-Oriented and Non-Consumer-Oriented Industries

Unlike traditional disclosure channels that focus on investors, disclosure via social media focuses jointly on investors and consumers, so often includes both financial information and advertising. While the difference in audience can increase the risk of misinterpretation, advertising has the potential to engage investors as well (Madsen & Niessner, 2016). Therefore, it is worth investigating whether the impact of firms' social media activity on analyst following and properties of analyst forecasts varies if firms are consumer-oriented or not.

In my main analyses, I include industry fixed effects to isolate variance attributable solely to industry idiosyncrasy. In this analysis, to provide deeper understanding of the impact of information shared through social media on analyst following and properties of analyst forecasts, I investigate whether the findings of the main analyses are sensitive to firms' purpose for social media communication. To do so, I split the main sample into two subsamples consisting of observations in the two consumer-oriented industries (Retail Trade and Services) and observations in the other non-consumer-oriented industries. I then re-estimate the main analyses for the two subsamples, separately.

Table 10, columns (1) and (2), present the results from estimation of the analyst following model in Table 5 for subsamples that include observations from consumer-oriented and non-consumer-oriented industries. The impact of financial social media disclosure (*Financial_Tweets*) on analyst following is significantly positive ($p<0.10$ for consumer-oriented firms and $p<0.05$ for non-consumer-oriented firms), regardless of the industry composition of the sub-samples. The economic significance of *Financial_Tweets* is greater in the non-consumer-oriented subsample. One interpretation is that the firms in these industries provide more effective investor relations information via social media disclosure. *Non-financial_Tweets* is negative and significant ($p<0.01$), but only for the subsample of firms in consumer-oriented industries. One interpretation is that, regardless of industries, financial social media disclosure provides value relevant information to financial analysts. However, social media disclosure is often context specific (Blankespoor, 2018) and a difference in the audience can increase the risk of misinterpretation (Madsen & Niessner, 2016). This may in turn reduce the incentives of financial analysts to follow a firm with greater nonfinancial social media disclosure in consumer-oriented industries. Together these findings indicate that social media disclosure provides a channel for companies to communicate with different groups of stakeholders at the same time. *Crowd_Tweets* is consistently not significant. *News and Size* have a positive association (all $p<0.01$) with analyst following for both subsamples, as was true of the main analysis. *Management forecasts* is positive and significant (p<0.05) only for the subsample of non-consumer-oriented firms.

Table 11 estimates the forecast error model presented in Table 6 for the two subsamples. With some exceptions, the results are qualitatively similar to those in Table 6. As is true of the main analysis, *Financial_Tweets* is negative and significant (all p<0.10) for both subsamples. This indicates that financial information disclosed through social media provide value relevant information for financial analysts, regardless of whether the firm is in a consumer-oriented or non-consumer-oriented industry. Similar to the results from the main analyses, *Non-financial_Tweets* is not significantly associated with analyst forecast errors for the non-consumer-oriented subsample. However, *Non-financial_Tweets* is negatively and significantly (p<0.10) associated with analyst forecast error for the subsample of consumer-oriented industries. This indicates that for the firms in the consumer-oriented industries, nonfinancial social media disclosures by the firm provide analysts with value relevant information. *Crowd_Tweets* is positive and significant (p<0.01 for consumer-oriented firms and p<0.05 for non-consumer-oriented firms). This implies that information from the crowd may mislead or add noise to the information mosaic of analysts. Alternatively, the volume of tweets by the crowd are a proxy for market participants' disagreement about the firm's future prospects. *Size* is negatively and significantly (p<0.05 for consumer-oriented firms and p<0.10 for non-consumer-oriented firms) associated with forecast error, while *Loss* (p<0.05 for consumer-oriented firms and p<0.01 for non-consumer-oriented firms) and *ROA* (p<0.10 for consumer-oriented firms and p<0.01 for non-consumer-oriented firms) are positively and significantly associated with forecast error. These findings indicate that firms with superior performance have richer information environments. Also, many of the control variables are consistent with the results in the main model. An exception is *Intangible Asset*, which is significant only in the subsample of firms in consumer-oriented industries.

Table 12 presents the analyst forecast dispersion analyses for the two subsamples. None of the three types of social media disclosure is significantly associated with analyst forecast dispersion in either subsample. In contrast, the results in Table 11 indicate that forecast errors are lower, the higher the volume of *Financial_Tweets*. Together, these findings imply that social media usage is associated with improved forecast accuracy, but that the additional information does not lead to a decrease in the heterogeneity of analyst beliefs. Overall, the subsample results are qualitatively similar to those reported in the primary analyses. Thus, I continue to find that financial information released by firms through Twitter is relevant to financial analysts, regardless of industry. However, the significance of some control variables differs between two subsamples.

5.2. Analysis of the Market Response to Analyst Forecast Revisions using 3-Day CARs

I also consider the sensitivity of my main results to the length of my event window. Gleason and Lee (2003) and Clement and Tse (2003) examine the market response to analyst forecast revisions using 3-Day Cumulative Abnormal Returns (CARs). In contrast, I use 2-Day CARs in my main tests. In this sub-section, I present market response results using 3-day CARs.

Table 13 presents results from the estimation of the model in Table 9 with 3-Day CARs as the dependent variable. These results show that the impact of analyst forecast revisions (*Mean_AFRevise*) is consistently significantly positive ($p<0.01$ for columns (1) and (2), and $p<0.05$ for column (3)) in all three specifications. The coefficient on *Log_Financial_Tweet* is negative and significant ($p<0.05$). Similar to the main analyses, the interaction term between analyst forecast revisions and social media disclosure (*Mean_AFRevise* * *Log_Fiancial_Tweet*) is positively and significantly ($p<0.10$) associated with the market response. Also similar to the main analyses, the coefficient on the amount of financial information provided by registered formal news organizations (*News*) is positive and significant ($p<0.01$), while the coefficient on *Size* is negative and significant ($p<0.01$). The coefficients on the number of analysts who issue a revision on the forecast revision date (*Total_Revise*) are now statistically significant ($p<0.10$).

5.3. Analysis of the Market Response to Analyst Forecast Revisions for Subsamples with and without Prior Management Forecasts

Previous studies find not only that stock prices significantly respond to management forecasts (Baginski and Hassell, 1990; Rogers and Stocken, 2005; Hirst, Koonce, and Venkataraman, 2008) but also that prior earnings forecasts by management influence subsequent financial analyst forecast revisions (Baginski and Hassell, 1990). To control for the confounding effect of management forecasts, my main analyses include an indicator variable (*Management_Ind*) that equals 1 when there is at least one management forecast of earnings in the period between the previous analyst forecast revision and the current analyst forecast revision. To more fully understand the potential influence of management forecasts on the market response to financial analyst earnings forecasts, I reexamine the market response to analyst forecast revisions for two subsamples which consists of observations that have a value of 1 and 0 for *Management_Ind*.

Table 14 reproduces the results presented in Table 9 using these subsamples. Column (1) and column (2) present the results for the subsamples with and without management forecast between the previous analyst forecast and the current analyst forecast revision, respectively. Analyst forecast revisions (*Mean_AFRevise*) and the interaction term between analyst forecast revisions and social media disclosure of financial information (*Mean_AFRevise * Log_Financial_Tweet*) are positively and significantly associated with 2-day window CARs for both subsamples (all $p<0.05$ for column (1) and all $p<0.10$ for column (2)).

*Mean_AFRevise*Log_Financial_Tweet*, the interaction term between the forecast revision and the volume of financial tweets, are positively and significantly (all $p<0.10$) associated with the market response to forecast revisions, regardless of whether a management forecast was issued between the previous analyst forecast and the current analyst forecast revision. In addition, the impact of the control variables does not vary much across the two subsamples. For example, *News* is positively and significantly associated with the market response (all $p<0.10$) for both subsamples. This indicates that investors still acquire value relevant information from traditional news organizations.

After noting that the coefficient on the interaction term is larger in the subsample of observations with no confounding release of a management forecast during the revision period, I construct a formal test of whether financial tweets have a larger impact on forecast revisions in the absence of concurrent management forecast. I include a 3-way interaction term of *Mean_AFRevise*Log_Finanacial_Tweet*Management_Ind* in the model and re-estimate the results for the full sample. The 3-way interaction term is significant and negative ($p<0.05$), which indicates that financial tweets have a larger impact on the market response to the forecast revisions in the absence of concurrent management forecast. Investors rely more on financial information provided by firms through social media when there is less information disclosed by management in other formats such as management forecasts.

6. CONCLUSION

This paper studies the effect of social media disclosure on the demand for financial analysts as information intermediaries. I measure the amount of social media disclosure by the firm as the number of tweets on financial and nonfinancial topics from the firm's Twitter account and the amount of social media disclosure about the firm by the public as the number of tweets that contain the firm's Cashtag.

I find that analyst following is larger and forecast errors are smaller, the larger the number of financial tweets by the firm. Analyst following is smaller, the larger the number of nonfinancial tweets by the firm. Forecast errors are larger, the larger the number of tweets by the public, while the volume of tweets by the public is not significantly associated with analyst following. Forecast dispersion is unassociated any of the three social media disclosure measures. Collectively, the findings suggest that only financial social media disclosure by the firm provides timely, value-relevant information to analysts.

I also provide evidence on the relation between social media disclosures and the market response to analyst forecast revisions. The coefficients on the revision variable and the interaction between the revision variable and the log of the number of financial tweets variable are both positive and significant. The significance of the interaction term implies that the higher the level of social media activity, the greater the association between analysts' forecast revisions and the market response to the revisions. In addition, the higher the level of a forecast revision, the greater is the association between social media activity and market response. The coefficient on the number of tweets is insignificant, consistent with the previous impounding of information in those tweets.

Results of this study also suggest that even though S&P 500 firms have significant media attention, interpretation of social media information by analysts is valuable. Prior studies show that social media is an efficient conduit for disseminating information to financial markets and affects investor behavior. However, there has been little scrutiny of how information on social media affects the behavior and beliefs of sophisticated information intermediaries. To my knowledge, this is also the first study to examine concurrently the influence of social media disclosures by firms and the public on financial analyst following and the properties of analyst earnings forecasts.

In closing, I mention two limitations of the study. First, this study provides descriptive associations, but does not establish a causal relation between social media disclosure and either analyst following or the properties of analyst earnings forecasts. Proving causality would require knowledge of whether and how an individual analyst improves his (her) forecasting process owing to social media disclosure. However, the results from the two-day market reaction tests are consistent with analysts using social media disclosures to form and revise their forecasts. Second, although I control for the number of news media articles about the firm, the number of Form 8-K filings, and the release of management earnings forecasts, the documented association between social media disclosure and analyst following and the properties of analyst earnings forecasts might be due to other information sources, as opposed to the increased volume of information on Twitter.

Despite these caveats, overall, this paper increases our understanding of how social media affects sophisticated information intermediaries such as financial analysts. In particular, this study provides evidence that both financial analysts and social media disclosures contribute to the flow of information.

APPENDICES

APPENDIX A

Variable Definitions and Data Sources

APPENDIX A. Variable Definitions and Data Sources

Variable	Definition	Data Source
Financial_Tweets	Number of financial tweets from a firm's official Twitter account that are sent during the fiscal quarter and contain financial key words.	Twitter via CrimsonHexagon
Non-financial_Tweets	Number of non-financial tweets from a firm's official Twitter account that are sent during the fiscal quarter and do not contain financial key words.	Twitter via CrimsonHexagon
Crowd_Tweets	Number of tweets containing the firm's Casthtag (i.e., $Ticker) sent by any account except the firm's official Twitter account during the fiscal quarter. *Crowd_Tweets* is scaled by 100.	Twitter via CrimsonHexagon
Following	Number of analysts who comprise the most recent I/B/E/S consensus quarterly earnings forecast prior to the quarterly fiscal period ending date.	I/B/E/S Summary
Forecast Error	Absolute difference between I/B/E/S actual reported earnings and the most recent I/B/E/S quarterly earnings median consensus forecast prior to the quarterly fiscal period ending date, scaled by actual reported earnings.	I/B/E/S Summary
Forecast Dispersion	Standard deviation of the individual analyst forecasts in the most recent I/B/E/S quarterly earnings median consensus forecast prior to the quarterly fiscal period ending date.	I/B/E/S Summary
CAR(0,1)	Abnormal daily returns cumulated over the two-day window beginning on the date that the forecast revision is released. Market-adjusted daily abnormal returns are calculated as the firm-specific returns less the CRSP value-weighted returns.	CRSP
Mean_AFRevise	The average news about the firm's expected earnings on Day t, defined as the mean analyst forecast revision on day t scaled by one-month prior stock price. For each individual sell-side analyst *i*, firm *j* and on day *t*, analyst forecast (AF) revision is measured as ($AF_{i,j,t}$ - $AF_{i,j,t-n}$), where $AF_{i,j,t-n}$ is the latest earnings forecast by analyst *i* for firm *j* prior to $AF_{i,j,t}$. If there are multiple individual analyst	I/B/E/S Detail, CRSP

	forecast revisions for firm *j* on day *t*, I use the average of the day *t* revisions. Analyst forecasts and stock price are adjusted for stock splits.	
Log_Financial_Tweet	Log of one plus the total number of the firm's Financial Tweets between the prior analyst forecast and the current analyst forecast revision.	Twitter via CrimsonHexagon
Mean_AFRevise Log_Financial_Tweet*	Interaction between Mean_AFRevise and Log_Financial_Tweet.	CRSP, Twitter via CrimsonHexagon
News	Log of one plus the total number of financial news articles during the fiscal quarter that contain the firm's official name and financial key words. Obtained from CrimsonHexagon's 'News' content source option, which provides full access to all the available "Fact-based articles by formal news organizations, such as CNN, New York Times, Wall Street Journal, etc." In the market response tests, *News* is measured as the Log of one plus the total number of financial news articles that contain a firm's official name and financial key words between the previous and the current analyst forecast revision dates.	News via CrimsonHexagon
Size	Log of market value as of the ending date of the fiscal quarter. For the market response tests, market capitalization is as of quarter t-1, where quarter t is the quarter in which the analyst forecast revision is released.	Compustat Quarterly
BtoM	Book value of equity as of the end of the fiscal quarter, divided by market value of equity as of the end of the quarter. In the market response tests, *BtoM* is measured as of the beginning of the quarter in which the analyst forecast revision is released.	Compustat Quarterly
Loss	Indicator variable equal to 1 if quarterly net income is negative and 0 otherwise.	Compustat Quarterly
ROA	Return on assets, as of the end of the fiscal quarter. Calculated by dividing net income by total assets.	Compustat Quarterly
Leverage	Financial leverage, calculated as the ratio of total liabilities to total assets as of end of the fiscal quarter. In the market	Compustat Quarterly

	response tests, Leverage is measured as of the beginning of the quarter in which the analyst forecast revision is released.	
Intangible Asset	Total intangible assets scaled by total assets, measured as of end of a quarter.	Compustat Quarterly
R&D	Quarterly research and development expense. Missing R&D expenses are set to be zero.	Compustat Quarterly
Bus_Seg	Number of reported business segments as of the ending date of the previous fiscal year.	Compustat Segments
Geo_Seg	Number of reported geographic segments as of the ending date of the previous fiscal year.	Compustat Segments
Institutional	Level of institutional holdings. Percentage of a firm's shares that are held by institutions as of the calendar quarter ending date.	Thomson Reuters Financial 13F data
Horizon	Number of days elapsed between the forecast date and the related earnings announcement date.	I/B/E/S Summary
8-K	Number of 8-K filings by a firm in each quarter. In the market response tests, *8-K* is measured as the number of 8-Ks filed by each firm between the prior analyst forecast and the current analyst forecast revision.	EDGAR
Management_Qtr	Number of management forecasts of EPS issued per quarter.	I/B/E/S Guidance
Management_Ind	Indicator variable equals to 1 if there is at least one management forecast of EPS issued between the period of the previous and current forecast revisions, 0 otherwise.	I/B/E/S Guidance
Total_Revise	The number of analysts who issue a revision on the forecast revision date. Total number of revisions is used to calculated *Mean_AFRevise*	I/B/E/S Detail

APPENDIX B

Industry Classifications

APPENDIX B. Industry Classifications[27]

Range of SIC Codes	Division
0100-0999	Agriculture, Forestry and Fishing
1000-1499	Mining
1500-1799	Construction
1800-1999	not used
2000-3999	Manufacturing
4000-4999	Transportation, Communications, Electric, Gas and Sanitary service
5000-5199	Wholesale Trade
5200-5999	Retail Trade
6000-6799	Finance, Insurance and Real Estate
7000-8999	Services
9100-9729	Public Administration
9900-9999	Nonclassifiable

[27] See https://www.osha.gov/pls/imis/sic_manual.html and http://www.ehso.com/siccodes.php

APPENDIX C

Tables

Table 1. Sample Selection

The final sample consists of 4,974 firm-quarter observations on 435 S&P 500 firms over the period 2012 – 2014.

	Firm-Quarters	Firms
Firm quarter observations in 2012, 2013, and 2014	6,000	500
Less observations from firms without official Twitter accounts linked to their official company Website	(780)	(65)
Less observations missing the data necessary to calculate the control variables	(237)	(0)
Less: observations with missing data needed to estimate dependent variables	(9)	(0)
Final sample used in the analyses	4,974	435

Table 2. Descriptive Statistics

This table reports descriptive statistics for the sample 4,974 firm-quarter observations on 435 S&P 500 firms over the period 2012 – 2014. Variable definitions are available in Appendix A.

Variable	Obs	Mean	Std. Dev.	Min	Median	Max
Financial_Tweets	4,974	143.075	35.341	92.000	133.000	211.000
Non-financial_Tweets	4,974	267.359	78.869	135.000	275.000	392.000
Crowd_Tweets	4,974	52.457	27.340	30.000	37.000	118.000
News	4,974	4.700	2.187	1.099	4.595	12.089
Following	4,974	18.317	7.728	3.000	19.000	38.000
Error	4,974	0.137	0.286	0.000	0.040	2.111
Dispersion	4,974	0.048	0.055	0.000	0.030	0.320
Horizon	4,974	12.840	12.480	8.000	12.000	31.000
Size	4,974	4.241	0.425	3.471	4.288	5.411
BtoM	4,974	0.466	0.401	-1.593	0.322	6.861
Loss	4,974	0.058	0.234	0.000	0.000	1.000
ROA	4,974	0.017	0.017	-0.038	0.012	0.080
Leverage	4,974	0.618	0.200	0.146	0.661	1.659
Intangible Asset	4,974	0.717	0.134	0.309	0.596	0.914
R&D	4,974	107.070	306.388	0.000	31.804	1933.000
Business_Seg	4,974	3.336	2.643	1.000	3.000	15.000
Geo_Seg	4,974	1.206	1.207	1.000	1.000	12.000
Institutional	4,974	0.715	0.135	0.309	0.725	1.000
8-K	4,974	3.599	2.359	0.000	3.000	13.000
Management_Qtr	4,974	1.246	0.584	1.000	1.000	9.000

Table 3. Profile Analysis

This table reports mean and median firm characteristics for firms in the top and bottom quartile of *Financial_Tweet* volume in the first quarter of 2014. The numbers in parentheses denote the medians and z-stats from the Wilcoxon rank-sum tests of quartile differences. The symbols ***, **, and * denote significance at 1%, 5%, and 10%, respectively. Variables are defined in Appendix A.

	Financial_Tweets = Low 25% volume	Financial_Tweets = High 25% volume	
Variable	Mean value of (Median value of)	Mean value of (Median value of)	t-test (Wilcoxon test)
Non-financial_Tweets	236.700	345.251	-8.239***
	(0.000)	(362.000)	(-14.222)***
Crowd_Tweets	59.490	96.925	-2.515***
	(32.000)	(45. 000)	(-5.770)***
News	6.138	7.028	-6.086***
	(6.216)	(6.939)	(-6.406)***
Following	17.023	20.059	-2.957***
	(16.000)	(20.000)	(-3.218)***
Error	0.117	0.123	-0.249
	(0.086)	(0.070)	(0.668)
Dispersion	0.055	0.045	1.523*
	(0.034)	(0.030)	(1.760)*
Horizon	11.881	12.068	-2.131**
	(12.000)	(12.000)	(-1.419)
Size	4.196	4.439	-4.310***
	(4.136)	(4.332)	(-4.102)***
BtoM	0.458	0.384	1.910**
	(0.396)	(0.305)	(2.231)**
Loss	0.063	0.052	0.493
	(0.000)	(0.000)	(1.283)
ROA	0.016	0.017	-0.359
	(0.014)	(0.013)	(-0.078)
Leverage	0.580	0.669	-3.597***
	(0.563)	(0.676)	(-3.947)***
Intangible Asset	0.313	0.312	0.035
	(0.361)	(0.338)	(-0.459)
R&D	62.767	171.775	-2.522***
	(0.000)	(0.000)	(-0.656)

Table 3 (cont'd)

Variable	Financial_Tweets = Low 25% volume Mean value of (Median value of)	Financial_Tweets = High 25% volume Mean value of (Median value of)	t-test (Wilcoxon test)
Business_Seg	3.194	2.732	1.617*
	(3.000)	(1.000)	(2.124)**
Geo_Seg	3.685	2.675	3.146***
	(3.000)	(2.000)	(3.147)***
Institutional	0.681	0.640	2.513***
	(0.699)	(0.647)	(2.925)***
8-K	3.468	3.925	-1.805**
	(3.000)	(3.000)	(-1.024)
Management_Qtr	1.245	1.000	0.842
	(1.000)	(1.000)	0.977
Observation	124	123	

Table 4. Pairwise Correlations among Variables Used in the Analysis

This table reports Pairwise correlations for the complete sample of 4,974 firm-quarter observations on 435 S&P 500 firms over the period 2012 – 2014. The coefficients in bold italics are significant at least at the 5% level. Variable definitions are provided in Appendix A.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1)*Financial_Tweets*	1.000									
(2) *Non-financial_Tweets*	***0.735***	1.000								
(3) *Crowd_Tweets*	***0.083***	***0.122***	1.000							
(4) *News*	***0.272***	***0.276***	***0.290***	1.000						
(5) *Following*	***0.165***	***0.167***	***0.163***	***0.367***	1.000					
(6) *Error*	***-0.075***	***-0.066***	***0.031***	0.013	***-0.138***	1.000				
(7) *Dispersion*	***-0.071***	***-0.069***	***0.050***	***-0.042***	-0.023	***0.290***	1.000			
(8) *Horizon*	***-0.034***	0.009	***-0.375***	***0.044***	-0.005	0.020	-0.004	1.000		
(9) *Size*	***0.156***	***0.136***	***0.288***	***0.455***	***0.334***	***-0.140***	***0.064***	***-0.047***	1.000	
(10) *BtoM*	***-0.081***	***-0.124***	***-0.031***	***-0.040***	***-0.032***	***0.203***	***0.274***	0.017	***-0.137***	1.000
(11) *Loss*	***-0.033***	***-0.028***	0.022	0.006	0.001	***0.285***	***0.099***	0.015	***-0.092***	***0.128***
(12) *ROA*	***0.053***	***0.083***	0.024	***0.077***	***0.113***	***-0.212***	***-0.105***	-0.002	***0.136***	***-0.460***
(13) *Leverage*	***0.080***	-0.017	-0.014	***0.054***	***-0.177***	0.022	***0.027***	-0.005	***-0.031***	***0.063***
(14) *Intangible Asset*	0.008	***-0.046***	***-0.029***	***0.268***	-0.002	***-0.168***	***-0.293***	-0.002	***0.034***	***-0.024***
(15) *R&D*	0.019	0.015	***0.229***	***0.271***	***0.216***	***-0.053***	***-0.028***	-0.021	***0.457***	***-0.139***
(16) *Business_Seg*	***-0.060***	***-0.069***	***0.029***	0.018	***-0.073***	***-0.044***	-0.021	-0.005	*0.121*	***0.070***
(17) *Geo_Seg*	***-0.100***	***-0.089***	0.007	***-0.040***	***0.082***	***-0.045***	0.001	0.005	***0.060***	***-0.052***
(18) *Institutional*	***-0.115***	***-0.097***	***-0.213***	***-0.243***	***0.030***	***0.085***	***0.031***	***0.104***	***-0.360***	***-0.079***
(19) *8-K*	***0.033***	-0.010	*0.040*	0.031	***0.033***	***0.086***	***0.145***	-0.003	***0.074***	***0.242***
(20) *Management_Qtr*	-0.062	-0.062	-0.089	0.026	0.024	-0.089	-0.032	-0.102	-0.022	***-0.129***

Table 4 (cont'd)

	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
(1)*Financial_Tweets*										
(2) *Non-financial_Tweets*										
(3) *Crowd_Tweets*										
(4) *News*										
(5) *Following*										
(6) *Error*										
(7) *Dispersion*										
(8) *Horizon*										
(9) *Size*										
(10) *BtoM*										
(11) *Loss*	1.000									
(12) *ROA*	***-0.448***	1.000								
(13) *Leverage*	***0.044***	***-0.275***	1.000							
(14) *Intangible Asset*	***-0.038***	***0.034***	***-0.135***	1.000						
(15) *R&D*	-0.002	***0.110***	***-0.141***	***0.093***	1.000					
(16) *Business_Seg*	***-0.028***	***-0.048***	-0.013	***0.015***	***0.175***	1.000				
(17) *Geo_Seg*	0.004	***0.082***	***-0.229***	***0.104***	***0.188***	***0.108***	1.000			
(18) *Institutional*	***0.046***	***0.032***	***-0.119***	***0.087***	***-0.154***	***-0.078***	0.021	1.000		
(19) *8-K*	***0.056***	***-0.196***	***0.206***	***-0.114***	***-0.050***	0.013	***-0.059***	***-0.061***	1.000	
(20) *Management_Qtr*	-0.043	***0.201***	0.041	-0.111	-0.101	0.031	***-0.133***	0.039	0.056	1.000

Table 5. Analyst Following Regression Analysis

This table reports the results of the negative binomial regression of analyst following on Twitter related variables and controls. The symbols ***, **, and * denote significance at 1%, 5%, and 10% based on two-tailed tests, respectively. To enhance the readability of the results, the Twitter related variables and R&D are scaled by 1000 and 10,000 respectively. The numbers in parentheses denote robust standard errors. Variable definitions are available in Appendix A.

VARIABLES	(1)		(2)	
Financial_Tweets			135.331	**
			(55.255)	
Non-financial_Tweets			-0.076	***
			(0.022)	
Crowd_Tweets			-0.002	
			(0.001)	
News	0.034	***	0.035	***
	(0.006)		(0.006)	
Size	0.274	***	0.303	***
	(0.036)		(0.038)	
BtoM	0.091	***	0.071	***
	(0.054)		(0.005)	
Loss	-0.033		-0.036	
	(0.049)		(0.049)	
ROA	1.245	*	1.288	*
	(0.717)		(0.722)	
Leverage	-0.635	***	-0.640	***
	(0.066)		(0.065)	
Intangible Asset	-0.048		-0.049	
	(0.058)		(0.058)	
R&D	0.050		0.030	
	(0.034)		(0.035)	
Business_Seg	-0.013	***	-0.014	***
	(0.004)		(0.004)	
Geo_Seg	-0.004		-0.005	
	(0.004)		(0.004)	
Institutional	0.529	***	0.499	***
	(0.091)		(0.091)	
8-K	-0.004		-0.004	
	(0.005)		(0.005)	
Management_Qtr	0.004		0.002	
	(0.013)		(0.013)	
Constant	1.611	***	1.501	***
	(0.194)		(0.196)	
Observations	4,974		4,974	
Pseudo R-squared	0.090		0.092	

Table 5 (cont'd)

Industry Indicators	YES	YES
Time Indicators	YES	YES

Table 6. Analyst Forecast Error Regression Analysis

This table reports the results of the ordinary least square regression of analyst forecast errors on Twitter related variables and controls. The symbols ***, **, and * denote significance at 1%, 5%, and 10% based on two-tailed tests, respectively. The Twitter related variables and R&D are scaled by 1000 and 10,000 respectively. The numbers in parentheses denote robust standard errors. Variable definitions are provided in Appendix A.

VARIABLES	(1)		(2)	
Financial_Tweets			-25.466	*
			(14.262)	
Non-financial_Tweets			0.003	
			(0.005)	
Crowd_Tweets			0.002	***
			(0.000)	
News	-0.001		-0.001	
	(0.003)		(0.003)	
Following	-0.004	**	-0.004	**
	(0.000)		(0.000)	
Horizon	-0.002		-0.001	
	(0.002)		(0.002)	
Size	-0.069	***	-0.055	**
	(0.024)		(0.022)	
BtoM	0.109	***	0.106	***
	(0.034)		(0.033)	
Loss	0.060	***	0.053	***
	(0.021)		(0.020)	
ROA	1.342	***	1.191	**
	(0.498)		(0.471)	
Leverage	0.044	*	0.037	
	(0.026)		(0.026)	
Intangible Asset	-0.054	**	-0.052	**
	(0.022)		(0.022)	
R&D	0.045	***	0.047	***
	(0.015)		(0.015)	
Business_Seg	-0.003		-0.002	
	(0.002)		(0.002)	
Geo_Seg	0.001		0.002	
	(0.002)		(0.002)	
Institutional	0.123	***	0.124	***
	(0.047)		(0.047)	
8-K	0.008	***	0.007	***
	(0.002)		(0.002)	
Management_Qtr	-0.009	**	-0.009	**
	(0.004)		(0.004)	

Table 6 (cont'd)

Constant	0.141	0.168
	(0.102)	(0.115)
Observations	4,974	4,974
Adjusted R-squared	0.214	0.216
Industry Indicators	YES	YES
Time Indicators	YES	YES

Table 7. Analyst Forecast Dispersion Regression Analysis

This table reports the results of ordinary least square regression of forecast dispersion on Twitter related variables and controls. The symbols ***, **, and * denote significance at 1%, 5%, and 10% based on two-tailed tests, respectively. To enhance the readability of the results, the Twitter related variables and R&D are scaled by 1000 and 10,000 respectively. The numbers in parentheses denote robust standard errors. Variable definitions are provided in Appendix A.

VARIABLES	(1)		(2)	
Financial_Tweets			8.781	
			(16.880)	
Non-financial_Tweets			-0.004	
			(0.004)	
Crowd_Tweets			0.000	
			(0.000)	
News	0.001		0.001	
	(0.002)		(0.001)	
Following	-0.001	***	-0.001	***
	(0.000)		(0.000)	
Horizon	0.002		0.003	
	(0.002)		(0.002)	
Size	0.004		0.003	
	(0.001)		(0.011)	
BtoM	0.045	**	0.045	**
	(0.018)		(0.018)	
Loss	0.039		0.038	
	(0.025)		(0.025)	
ROA	-0.003		-0.032	
	(0.410)		(0.425)	
Leverage	-0.016		-0.018	
	(0.015)		(0.016)	
Intangible Asset	-0.042	***	-0.042	***
	(0.012)		(0.012)	
R&D	-0.005		-0.006	
	(0.006)		(0.007)	
Business_Seg	0.002		0.002	
	(0.002)		(0.002)	
Geo_Seg	0.001		0.001	
	(0.002)		(0.002)	
Institutional	0.007		0.006	
	(0.016)		(0.015)	
8-K	-0.000		-0.000	
	(0.001)		(0.001)	
Management_Qtr	0.003		0.003	
	(0.003)		(0.003)	
Constant	-0.015		-0.014	

Table 7 (cont'd)

	(0.069)	(0.072)
Observations	4,974	4,974
Adjusted R-squared	0.224	0.235
Industry Indicators	YES	YES
Time Indicators	YES	YES

Table 8. Descriptive Statistics for Variables Used in the Market Response Analysis

This table reports descriptive statistics for the variables used in the market response analysis. Variable definitions are provided in Appendix A.

Variable	Obs	Mean	Std. Dev.	Min	Median	Max
CAR(0,1)	25,835	0.005	2.467	-36.101	-0.001	29.734
Mean_AFRevise	25,835	-0.001	0.011	-1.151	-0.001	0.208
*Mean_AFRevise*Log_Financial_Tweet*	25,835	0.000	0.010	-0.393	0.000	0.400
Log_Financial_Tweet	25,835	1.474	1.469	0.000	1.386	8.304
News	25,835	1.243	1.187	0.000	1.946	3.019
Size	25,835	9.878	1.075	5.438	9.774	13.348
BtoM	25,835	0.468	0.365	-0.441	0.378	2.567
Leverage	25,835	0.600	0.195	0.081	0.588	1.652
Total_Revise	25,835	1.830	2.141	1.000	4.000	27.000
8-K	25,835	0.263	0.440	0.000	0.000	1.000
Management_Ind	25,835	0.099	0.299	0.000	0.000	1.000

Table 9. Regression Analysis of the Market Response to Analyst Forecast Revisions Using 2-Day CARs

This table reports the results of the ordinary least square regression analysis of the market response to analyst forecast revisions. The symbols ***, **, and * denote significance at 1%, 5%, and 10% based on two-tailed tests, respectively. To enhance the readability of the results, the dependent variable, *CAR(0,1)*, is multiplied by 100. The numbers in parentheses denote robust standard errors. Variable definitions are provided in Appendix A.

VARIABLES	(1)		(2)		(3)	
Mean_AFRevise	12.492	***	12.564	***	7.756	**
	(3.284)		(3.284)		(3.692)	
Mean_AFRevise Log_Financial_Tweet*					7.351	*
					(4.204)	
Log_Financial_Tweet			-0.010		-0.010	
			(0.011)		(0.010)	
News	0.013	*	0.018	**	0.018	**
	(0.007)		(0.007)		(0.007)	
Size	-0.049	***	-0.052	***	-0.051	***
	(0.016)		(0.016)		(0.016)	
BtoM	0.009		0.004		0.009	
	(0.047)		(0.047)		(0.047)	
Leverage	0.123		0.123		0.115	
	(0.080)		(0.080)		(0.079)	
Total_Revise	-0.004		-0.005		-0.005	
	(0.003)		(0.003)		(0.003)	
8-K	0.038		0.040		0.040	
	(0.053)		(0.053)		(0.053)	
Management_Ind	-0.009		-0.007		-0.009	
	(0.081)		(0.082)		(0.081)	
Constant	0.376	**	0.421	**	0.413	**
	(0.162)		(0.164)		(0.160)	
Observations	25,835		25,835		25,835	
Adjusted R-squared	0.005		0.006		0.008	

Table 10. Analyst Following Regression Analysis for Subsamples of Consumer-Oriented Industries and Non-Consumer-Oriented Industries

This table reports the results of the negative binomial regression of analyst following on Twitter related and control variables for subsamples of consumer-oriented industries and non-consumer-oriented industries. The symbols ***, **, and * denote significance at 1%, 5%, and 10% based on two-tailed tests, respectively. To enhance the readability of the results, the Twitter related variables and R&D are scaled by 1000 and 10,000 respectively. The numbers in parentheses denote robust standard errors. Variable definitions are available from Appendix A

VARIABLES	(1) Consumer-Oriented		(2) Non-Consumer-Oriented	
Financial_Tweets	122.512	*	346.949	**
	(72.312)		(66.464)	
Non-financial_Tweets	-0.232	***	-0.070	
	(0.073)		(0.068)	
Crowd_Tweets	-0.002		-0.001	
	(0.002)		(0.001)	
News	0.030	***	0.041	***
	(0.010)		(0.007)	
Size	0.417	***	0.212	***
	(0.052)		(0.041)	
BtoM	-0.047	***	0.274	***
	(0.008)		(0.006)	
Loss	-0.043		-0.008	
	(0.062)		(0.051)	
ROA	2.471	***	-0.675	
	(0.863)		(0.733)	
Leverage	-0.557	***	-0.880	***
	(0.093)		(0.072)	
Intangible Asset	-0.118		-0.001	
	(0.090)		(0.061)	
R&D	0.063		-0.060	
	(0.051)		(0.038)	
Business_Seg	-0.003		-0.025	***
	(0.005)		(0.004)	
Geo_Seg	0.002		-0.006	
	(0.007)		(0.005)	
Institutional	0.289	*	0.670	***
	(0.152)		(0.106)	
8-K	0.004		-0.010	*
	(0.009)		(0.005)	
Management_Qtr	0.001		0.030	**
	(0.019)		(0.015)	
Constant	2.585	***	0.731	***

Table 10 (cont'd)

	(0.256)	(0.201)
Observations	906	4,068
Pseudo R-squared	0.087	0.105
Industry Indicators	YES	YES
Time Indicators	YES	YES

Table 11. Analyst Forecast Error Regression Analysis for Subsamples of Consumer-Oriented Industries and Non-Consumer-Oriented Industries

This table reports the results of the ordinary least square regression of forecast error on Twitter related and control variables for subsamples of consumer-oriented and non-consumer-oriented industries. The symbols ***, **, and * denote significance at 1%, 5%, and 10% based on two-tailed tests, respectively. The Twitter related variables and R&D are scaled by 1000 and 10,000 respectively. The numbers in parentheses denote robust standard errors. Variable definitions are provided in Appendix A.

VARIABLES	(1) Consumer-Oriented		(2) Non-Consumer-Oriented	
Financial_Tweets	-27.012	*	-25.203	*
	(16.102)		(14.422)	
Non-financial_Tweets	-0.012	*	0.005	
	(0.007)		(0.005)	
Crowd_Tweets	0.005	***	0.002	**
	(0.002)		(0.001)	
News	-0.003		0.000	
	(0.005)		(0.003)	
Following	-0.006	***	-0.001	**
	(0.001)		(0.000)	
Horizon	0.002		-0.002	
	(0.003)		(0.002)	
Size	-0.061	**	-0.048	*
	(0.031)		(0.028)	
BtoM	0.151	***	0.055	
	(0.053)		(0.037)	
Loss	0.049	**	0.059	***
	(0.025)		(0.021)	
ROA	1.040	*	1.439	***
	(0.603)		(0.489)	
Leverage	0.050		0.035	
	(0.039)		(0.029)	
Intangible Asset	-0.115	***	-0.041	
	(0.010)		(0.033)	
R&D	0.099	***	0.037	**
	(0.027)		(0.017)	
Business_Seg	-0.002		-0.002	
	(0.003)		(0.002)	
Geo_Seg	0.001		0.002	
	(0.003)		(0.002)	
Institutional	0.167	***	0.101	**
	(0.061)		(0.050)	
8-K	0.008	***	0.007	***

Table 11 (cont'd)

Management_Qtr	-0.009 *	-0.009 **
	(0.005)	(0.004)
Constant	0.201	-0.097
	(0.159)	(0.101)
Observations	906	4,068
Adjusted R-squared	0.223	0.216
Industry Indicators	YES	YES
Time Indicators	YES	YES

Table 12. Analyst Forecast Dispersion Regression Analysis for Subsamples of Consumer-Oriented Industries and Non-Consumer-Oriented Industries

This table reports the results of ordinary least square regressions of forecast dispersion on Twitter related and control variables for subsamples of consumer-oriented and non-consumer-oriented industries. The symbols ***, **, and * denote significance at 1%, 5%, and 10% based on two-tailed tests, respectively. To enhance the readability of the results, the Twitter related variables and R&D are scaled by 1000 and 10,000 respectively. The numbers in parentheses denote robust standard errors. Variable definitions are provided in Appendix A.

VARIABLES	(1) Consumer-Oriented		(2) Non-Consumer-Oriented	
Financial_Tweets	6.213		9.597	
	(24.135)		(17.678)	
Non-financial_Tweets	-0.003		-0.004	
	(0.007)		(0.005)	
Crowd_Tweets	0.000		0.000	
	(0.000)		(0.000)	
News	0.001		0.002	
	(0.002)		(0.001)	
Following	-0.001	***	-0.001	***
	(0.000)		(0.000)	
Horizon	0.002		0.003	
	(0.003)		(0.002)	
Size	0.002		0.005	
	(0.021)		(0.014)	
BtoM	0.052	*	0.041	**
	(0.031)		(0.020)	
Loss	0.032		0.039	
	(0.036)		(0.028)	
ROA	-0.036		-0.028	
	(0.587)		(0.445)	
Leverage	-0.014		-0.025	
	(0.024)		(0.018)	
Intangible Asset	-0.043	**	-0.041	***
	(0.021)		(0.014)	
R&D	-0.005		-0.006	
	(0.012)		(0.008)	
Business_Seg	0.003		0.002	
	(0.004)		(0.002)	
Geo_Seg	-0.002		0.001	
	(0.003)		(0.002)	
Institutional	0.033		-0.006	
	(0.024)		(0.017)	
8-K	-0.001		-0.000	

Table 12 (cont'd)

	(0.002)	(0.001)
Management_Qtr	-0.001	0.003
	(0.004)	(0.003)
Constant	0.005	-0.045
	(0.092)	(0.084)
Observations	906	4,068
Adjusted R-squared	0.217	0.233
Industry Indicators	YES	YES
Time Indicators	YES	YES

Table 13. Regression Analysis of the Market Response to Analyst Forecast Revisions Using 3-day CARs

This table reports the results from ordinary least squares regression analysis of the market response to analyst forecast revisions using 3-day CARs. The symbols ***, **, and * denote significance at 1%, 5%, and 10% based on two-tailed tests, respectively. To enhance the readability of the results, the dependent variable, *CAR(-1,1)*, is multiplied by 100. The numbers in parentheses denote robust standard errors. Variable definitions are provided in Appendix A.

VARIABLES	(1)		(2)		(3)	
Mean_AFRevise	22.579	***	20.353	***	15.092	**
	(7.682)		(7.153)		(6.296)	
Mean_AFRevise Log_Financial_Tweet*					8.135	*
					(4.822)	
Log_Financial_Tweet			-0.033	**	-0.032	**
			(0.013)		(0.013)	
News	0.012	*	0.031	***	0.032	***
	(0.008)		(0.010)		(0.010)	
Size	-0.049	***	-0.078	***	-0.077	***
	(0.019)		(0.021)		(0.021)	
BtoM	-0.001		-0.002		0.004	
	(0.055)		(0.063)		(0.063)	
Leverage	-0.148		-0.099		-0.099	
	(0.111)		(0.133)		(0.134)	
Total_Revise	-0.005	*	-0.006	*	-0.006	*
	(0.003)		(0.004)		(0.004)	
8-K	0.121	**	0.095		0.096	
	(0.052)		(0.061)		(0.061)	
Management_Ind	0.034		0.017		0.0136	
	(0.081)		(0.095)		(0.095)	
Constant	0.497	***	0.735	***	0.720	***
	(0.187)		(0.212)		(0.212)	
Observations	25,835		25,835		25,835	
Adjusted R-squared	0.005		0.005		0.006	

Table 14. Regression Analysis of the Market Response to Analyst Forecast Revisions for Subsamples with and without Prior Management Forecasts Using 2-Day CARs

This table reports results of the ordinary least square regression of the market response to analyst forecast revisions on Twitter variables and control variables for subsamples with and without concurrent management forecasts (MF). The symbols ***, **, and * denote significance at 1%, 5%, and 10% based on two-tailed tests, respectively. To enhance the readability of the results, the dependent variable, *CAR(0,1)*, is multiplied by 100. The numbers in parentheses denote robust standard errors. Variable definitions are provided in Appendix A.

VARIABLES	(1) With MF		(2) Without MF		(3) Full Sample	
Mean_AFRevise	10.032	**	6.715	*	7.756	**
	(4.821)		(4.014)		(3.692)	
Mean_AFRevise Log_Financial_Tweet*	6.035	*	8.474	*	6.513	*
	(3.653)		(5.132)		(3.895)	
Log_Financial_Tweet	-0.008		-0.013		-0.010	
	(0.015)		(0.013)		(0.010)	
Mean_AFRevise Log_Financial_Tweet* Management_Ind*					-1.452	**
					(0.726)	
News	0.022	*	0.017	*	0.018	**
	(0.013)		(0.010)		(0.007)	
Size	-0.065	***	-0.032	*	-0.051	***
	(0.025)		(0.019)		(0.016)	
BtoM	-0.013		0.022		0.009	
	(0.065)		(0.053)		(0.047)	
Leverage	-0.008		0.141		0.115	
	(0.135)		(0.101)		(0.079)	
Total_Revise	-0.006		-0.005		-0.005	
	(0.006)		(0.005)		(0.003)	
8-K	-0.021		0.054		0.040	
	(0.068)		(0.057)		(0.053)	
Management_Ind					-0.009	
					(0.081)	
Constant	0.513	**	-0.083		0.411	**
	(0.250)		(0.192)		(0.160)	
Observations	10,647		15,188		25,835	
Adjusted R-squared	0.008		0.008		0.009	

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REFERENCES

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