8-K Filings, Twitter Activities and Stock Market Reactions

Abstract

Twitter has become one of the major channels for information dissemination and communication, which includes companies' market relevant information. This study investigates how Twitter activities are related to 8-K filings and the corresponding stock price and trading volume reactions. Using a sample of S&P 1500 companies, all 8-K filings are gathered for the calendar year of 2012 and calculate the following three unique Twitter metrics based on the data provided by Topsy, Inc.: abnormal tweeting activities, abnormal sentiment, and network centrality weighted by the influence level of tweeters. The findings show that on average, there are about 32% more tweeting activities around 8-K dates, compared to the benchmark period. In addition, all three Twitter metrics relate positively to both cumulative abnormal returns and cumulative abnormal trading volume in the 3-day window around 8-K filings. Abnormal sentiment and centrality weighted by the influence level of tweeters moderate positively and moderate negatively the association between abnormal tweeting activities and stock market reactions to 8-Ks. These metrics also moderate the relation between different types of 8-Ks and the corresponding stock market reactions. Based on our findings, we conclude that the level and nature of market attention a corporate announcement receives determines the level of price and volume movements of stocks in the capital markets. The study contributes to the literature by suggesting the important role played by social media, Twitter in particular, in the information dissemination process of Form 8-Ks.

Keywords: 8-K filings; social media; Twitter; abnormal returns; abnormal trading volume

JEL Classification: M41

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1 Introduction

Utilizing a unique dataset, this study investigates the market effect of tweet communication in periods when corporations make market relevant disclosures. The tweet communication examined in this study includes tweet activity, the sentiment expressed in those tweets and the importance in social networks of both tweeters and the corporations about which they tweet. We consider tweet communication because of the following reasons. Twitter has become a central mechanism for the rapid global distribution of information, including information about corporations. Over the last few years, the maximum of 140 characters in tweets has come to dominate real-time communication on all types of matters. Twitter reports that 0.5 billion tweets are communicated each day in its network of nearly 0.3 billion monthly active users (Twitter 2014). Twitter is the technological embodiment of the premise of Web 2.0, which conceptualizes the creation and exchange of content by any user. It allows for the instantaneous and unhindered generation and dissemination of content. Twitter, therefore, has created a setting of publicly observable communication and exchange of information, ideas and opinions on matters of everyday interest. Communication by and about corporations has been a feature of Twitter. The network enables companies to go beyond traditional modes of disclosures. It allows them to have direct communication with their stakeholders. Twitter received an additional boost when the SEC endorsed the use of Twitter and other social media for company announcements (SEC 2013). Further, it allows stakeholders and market participants to communicate among themselves about the companies.

Prior studies examining the behaviors of investors in stock markets can be categorized in two main streams: testing the efficient market hypothesis of rational human behavior and using behavioral approaches to understand how different individuals react to new information. The former draws inferences of the participants' behaviors by understanding the price and volume measures arising from corporate announcements. The latter, however, examines the investors' behaviors with the belief that individuals may react differently under different circumstances and may possess different priors through specified tasks in experiments. The Twitter setting provides a unique opportunity to bring the two streams of research together by observing actual communication exchange among companies, investors and other stakeholders. From the Twitter communication, it is possible to determine how investors and other stakeholders behave when new information is released by companies, and then relate the Twitter activities with stock market volume and price movements.

In this study we investigate Twitter activities around Form 8-K filing dates to ascertain to what extent investor and stakeholder conversation surrounding 8-K filings affect stock volume and price reactions to such filings. Form 8-K filings with the Securities and Exchange Commission (also known as "8-K filings") are used to notify investors regarding material current events, such as the change in executive management and changes in corporate governance or control of the company. We argue that the interactive communication through Twitter reflects the level of interest to information items in the 8-K filings and other associated information, and that such level of interest would affect the stock market reactions to the filings. In addition, the sentiment expressed in the tweets and the importance of the company weighted by the influence level of the tweeters who tweet about those companies would also reflect the level of interest in the company and the interpretation of the investors and stakeholder of the 8-K information. The level of interest and the nature of the interpretations can affect the decisions of the investors resulting in higher or lower stock market reactions to 8-K filings. We also interact these features of tweeter activities with different types of 8-K information to ascertain how the different types of 8-K information relate to these features.

In order to address our research objective, we collect a sample of S&P 1500 companies' 8-K filings in the calendar year of 2012. Based on this sample, we then measure (1) stock market reactions, and (2) Twitter metrics. For stock market reactions, we calculate cumulative abnormal returns and cumulative abnormal trading volume in the three-day window around 8-K filing dates. For Twitter metrics, we analyze two classes of metrics employing a proprietary database from Topsy, Inc[1]. The first

[1] Topsy Inc. takes a complete daily feed of all tweets and updates a master database (www.topsy.inc). Researchers can then conduct targeted searches over the database. Topsy is now part of Apple, Inc.

class of metrics relates to tweet activity in an event window around the 8-K announcement. We construct measures of abnormal tweet and retweet activity. While the level of activity is clearly of interest, the sentiment expressed in this conversation is of equal or greater valence. We measure abnormal changes in the sentiment levels of the tweets in the event window. The second class of metrics relate to the nature of parties tweeting about corporations. Parties tweeting about corporations ("tweeters") operate in a social network. The influence levels of those tweeters provide additional leverage to their tweets. Just as tweeters operate within a social network, so do the corporations which are the subjects of their tweets. We measure the centrality of each company in the tweeting social network.

Our results first demonstrate that, around 8-K filing dates, there are on average about 32% more tweeting activities and the sentiment level of the tweets is on average about 0.7% more positive. In addition, overall, we find significant positive association between abnormal tweeting activities, abnormal sentiment, as well as the importance of the companies weighted by the influence level in the tweeting network, and both stock price and trading volume reactions around 8-K filing dates. Our findings suggest that Twitter activities around 8-K filing dates play an important role in the information disseminating process of 8-K information that would be incorporated by market participants when forming and updating their investment decisions. Third, we show that Twitter activities would moderate each other's effects on both stock price and trading volume reactions. In particular, though abnormal tweeting activities or abnormal sentiment itself is an important factor for market reactions to 8-K filings, the change of sentiment of the content and the company's importance in the tweeting network after considering the influence level of the tweeter are also critical in responding to the 8-K information. Last, tweeting activities also moderate the association between 8-K types (operating results and off-balance sheet obligations, in particular) and stock market reactions, which suggests that Twitter activities can influence the market reaction to corporate announcements.

This study makes important contributions to the literatures on the role of social media, communication by market participants and market activity by (1) demonstrating how Twitter users react to companies' 8-K filings by interacting with the company and other users on Twitter, (2) providing the information diffusion processes after the release of companies' major events, and (3) how the influential tweeters, the sentiment of the tweeters and the importance of a company in the tweeting network in the information dissemination process are associated with market reactions to company announcements. The findings also have managerial insights because they shed light on the level of tweet activity, sentiment, influential tweeters, and the relative importance of corporations in social networks. These Twitter features are associated with the market reactions to the disclosures of material information.

The remainder of the paper is organized as follows. In Section 2, we review prior literature and discuss the communication features of Twitter as well as how these features help gauge the behaviors of investors and other stakeholders. Research methodology is discussed in Section 3. We present our results in Section 4. In Section 5, we set out our conclusions and lay out our future research plans.

2 Literature Review and Research Questions:

Our study examines the intervening impact of tweets on the market effects of a company's continuous disclosures on material events. Twitter is a form of micro blogging. It provides real-time communication between users through computers and mobile devices (Twitter.com 2014). Each tweet is limited to a maximum of only 140 characters. Tweets can be read by both registered and unregistered users, with registered users being able to respond to or redirect individual tweets. Twitter is increasingly observed in corporate and investment settings. For example, a recent study by Du and Jiang (2014) shows that 26% of S&P1500 index constituents have Twitter corporate profiles (28% have Facebook profiles). They find that the use of social media, and particularly for Facebook and Twitter, is associated with higher company valuation and company return on assets.

The effect of mandated and voluntary disclosures on the market has been extensively studied (Kothari 2001). These include voluntary disclosures made in periodic financial reports (e.g., Botosan 1997; Clarkson et al. 1994; Dietrich et al. 2001; Francis et al. 2008), conference calls (e.g., Brown et al. 2004; Bushee et al. 2003; Frankel et al. 1999), press releases (Kimbrough and Wang 2014) and video (Elliott et al. 2012). The current disclosures in our study are 8-K filings with the SEC. As a form of continuous disclosure, the Commission requires companies to file 8-Ks on a wide range of market relevant events shortly after they occur (see Appendix A for a list of types of 8-K filings). Examples of these events are exchange listings and delistings; entering into a material contract; acquisitions or dispositions of assets and changes in directors and senior management. The disclosures made in 8-Ks are representative of both traditional quarterly and annual financial performance, which are the focus of much of the literature on voluntary and mandated disclosure and which occur at defined intervals, as well as continuous disclosures. Following the mandate of Section 409 of the Sarbanes-Oxley Act, the SEC increased the range of material events that came within the scope of an 8-K filing and also reduced the period in which the filings must be made (SEC 2004). Lerman and Livnat (2010) observe that apart from increasing the scope of disclosures, the SOX Section 409 mandate effectively doubled the volume of such filings. They find that all types of 8-K disclosures are associated with abnormal market volume and price effects. This applied to "old" or "new" types of disclosures or when evaluating the disclosures at the filing or event dates. The 8-K disclosures to the SEC are appropriate vehicles to observe the effect of Twitter communications on the market. The 8-K disclosures draw the attention of the market participants observable through stock market volume and price reactions (Lerman and Livnat 2010). The link between 8-K disclosures and stock market reactions can be better explained by Twitter activity surrounding the 8-K disclosures, the Twitter activity being the sign of market interest in the disclosure.

A recent study by XXXX (Forthcoming), using Merton's (1987) Investor Recognition Hypothesis, finds that while corporate announcements are available through public sources, spread of corporate announcements through Twitter allows companies to attract investor attention. They argue that an increase in investor attention is associated with a decrease in information asymmetry caused by Twitter activity. They provide evidence for the reduced information asymmetry by showing that abnormal bid-ask spreads are lower when the abnormal levels of tweets are higher in the event period.

2.1 Tweet activity around corporate disclosure

The instantaneous latency and limited message size, coupled with ubiquitous availability of Tweet clients on mobile devices and computers makes Twitter an ideal channel for interactive communication. A specific advantage of Twitter is that it allows an open instantaneous online communication between parties interested on a topic and provides simple folksonomies, particularly hashtags (e.g., #earnings). Interactive communication in short messages can reveal the level of interest in a new information item by the number of tweets being sent, addition of new content, forwarding of tweets to others, the sentiments of the tweeters, the level of influence of the tweeters making those tweets and the central theme of the conversation in the tweets, etc. The effect of Twitter has been shown in a variety of settings including the market value of television programming (Nagy and Midha 2014); brand value (Kim et al. 2014) and the level of movie sales (Rui et al. 2013). In the particular context of corporate disclosure, Zhou et al. (2014, Forthcoming) study social media adoption by a sample of 9,861 US listed corporations. They find that 43% of these companies have corporate Twitter accounts. Many of these accounts are for subjects other than corporate disclosure (marketing, customer relations etc.). Zhou et al. (2014, Forthcoming) find that 3.5% of the 3.4m tweets issued by these accounts over the 2009-2013 were directly related to corporate disclosures. Given the importance and market relevance of 8-K disclosures, the engagement of corporations for disclosure purposes, and the omnipresence of Twitter, we expect that there 8-K disclosures will be associated with elevated levels of Twitter activity.

2.2 Market effects of tweet activity

There is limited evidence of market reaction to Twitter activity. Blankespoor et al. (2014), focusing on technology companies, studied the effects of using Twitter to send links to the press releases, earnings announcements, or conference calls and abnormal tweeting on abnormal bid-ask spread and abnormal depths (i.e., the number of quantitative disclosures). Their findings demonstrate that the distribution of news through Twitter is associated with lower abnormal bid-ask spread and larger abnormal depths. Curtis et al. (2014) investigate the correlation of social media activity, including Twitter and discussions on StockTwit.com, around earnings releases. They find that elevated levels of activity are associated with aggressive market response to earnings news.

We expect, then, to observe stock market reaction to 8-K filings are related to abnormal tweet activity around 8-K events. Specifically, the abnormal tweet activity reflects the change of tweeting activities around 8-K filing dates, compared to benchmark period. Given that Twitter activities reflect users' interests and attentions, this activity change shows possible interest or attention change with the release of 8-K information. Since the increase of attention has been shown to be related to stock price reactions we expect a positive relation between abnormal tweet activities and 8-K filing that is the increasing interest or attention around 8-K filing dates would be related to stock price reactions to 8-K filings.

In addition, we also expect abnormal tweeting activities to be related to trading volume reactions around 8-K filings. Beaver (1968) demonstrates that earnings announcements generate both high trading volume and abnormal stock price changes. The difference between stock price and trading volume reaction is that price change is about the market's average beliefs aggregately and trading volume behavior is the sum of individual investors' trade (i.e., counterbalanced beliefs among individual investors) (Bamber and Cheon 1995; Kim and Verrecchia 1991). For instance, Kim and Verrecchia (1991) analytically show that the trading volume behavior is because of different quality of information acquired and prior beliefs of the investors. In the Twitter context, the abnormal tweeting activities around 8-K filings provide more than just the number of tweets but possibly various pieces of information related to 8-Ks. The increased interest and attention along with various pieces of information may help market participants form or update their beliefs about the company. The different belief change of market participants may result in higher (abnormal) trading volume around 8-K filing dates. Accordingly, we expect a positive relation between trading volume reactions to 8-K filings and abnormal levels of tweeting activities around 8-Ks.

However, the amount of tweeting activities fails to capture two more important factors that may contribute to the explanations when analyzing Twitter communications on market participants' judgments and decisions around 8-K filings: sentiment and network influence level. Accordingly, we discuss these two factors regarding how they may moderate the abnormal tweeting activities in the next two sub-sections.

2.3 Sentiment

While tweets are limited to only 140 characters, they can and do express measurable sentiments (positive, neutral, negative). Understanding the sentiment of written communications can add explanatory power when analyzing the effects of those communications on human judgments and decisions. This applies when the unit of analysis is at either the individual or collective levels. At the individual level, the sentiment in messages can influence decision makers affective states and their decision making (Bonner 2008). Broader sentiment levels can also sway individual decision making. For example, Miller and Sedor (2013) show experimentally that the sentiment embedded in stock prices influences the rating decisions of analysts.

There is increasing evidence of the influence of sentiment at the collective level. An important strand in behavioral finance is the study of market participant sentiment on market levels and activity. Huang et al. (2014), apply machine learning techniques to the text in 0.4 million analyst reports. They find that the market, as measured by cumulative abnormal returns, reacts to the sentiment levels in those reports and, further, gives “twice the weight to negative as they do to positive text.”

In the past few years, there have been more research activities focusing on the role played by sentiment in tweets. For example, Jansen et al. (2009) study the effects of tweets on consumer behaviors and find that tweets can affect consumer brand image. Pak and Paroubek (2010) use Twitter for sentiment analysis and opinion mining, and build a sentiment classifier, which is able to determine positive, negative and neutral sentiments for tweets. Similarly, Rui et al. (2013) explore the effects of both frequency and sentiment, and find that both features affect consumer behaviors. Specific in our context, there are a limited number of studies that investigate investor behaviors on Twitter and the impact of such behaviors on stock prices. For example, Bollen et al. (2011) study the impact of the sentiment of tweeters on Dow Jones Industrial Average. They show that the accuracy of the Dow Jones Industrial Average prediction is improved by including sentiment information. Furthermore, Sul et al. (2014) used Twitter posts for S&P 500 companies and analyzed the cumulative emotional valence. Their results demonstrated that emotional valence of tweets is related to companies' stock returns. Such relation can be moderated by the number of followers suggesting the speed of the dissemination of emotion would affect stock prices.

2.4 Network influence levels

Communication on Twitter takes place within a social network (Scott 2013; Kadushin 2011; Jackson 2010). That is, a company can be viewed as an actor (a node) in the tweeting network. It connects to other companies (actors or nodes) through the tweets. The network can be dense, sparse or centralized. Participants in that network exert greater or lesser influence on other members of the network. In an early study, Cha et al. (2010) find that influence levels of tweeters can be measured on three independent vectors: the number of followers (termed indegree influence), number of retweets and the number of mentions of the tweeter's handle. It is possible for a tweeter to have a large number of followers but make very few tweets that influence the social network. Retweet influence is a measure of how collectively significant tweets are perceived by members of the network. Retweeting is a passive activity, however. Conversely, mention influence requires a tweeter to actively incorporate another tweeter's handle in the body of the tweet. Cha et al. (2010) show that these alternative measures of influence are essentially uncorrelated.

In the US setting, corporations are subject to severe limits by the SEC and common law as to how, when and where they may participate in social media and other forms of interaction on discussions that are relevant for market activity. While the SEC now allows corporations to use social media for investor relations purposes, there are strict limits on what a company may tweet or discuss on Facebook. Managers do not have open slather to enter into a twitter exchange on matters that directly relate to securities transactions, such as 8-K announcements. Corporate twitter accounts that directly relate to investor relations matters are essentially unidirectional, transmitting relevant information but not engaging in broader dialog.

Two concepts are directly related to our context: centrality and influence level. Centrality indicates a company's position in this tweeting system. That is, companies are connected through tweets. When a company has more direct and indirect connections in the tweeting network, the company has a higher level of centrality, i.e., more "important" in terms of showing with other companies more often in tweets. Specifically, often times, tweets will discuss several corporations, by referencing multiple stocktwits. This may be as a result of market relevant events that affect multiple corporations (e.g., changes in the price of raw materials) or where company-specific events will influence the valuation of other corporations (e.g., competitors or customers).

Given the restrictions on direct corporate participation discussed above, the influence of Twitter on investment related topics comes primarily from tweeters in the Twitter network. Tweeters convey their level of influence on the object of their tweets. As might be expected, tweeters who tweet on investment related topics do not necessarily restrict themselves to a single company. Rather, we observe tweeters who tweet on many corporations. We can observe the relative influence of Twitter discussion at the level of the individual company in the social network by analyzing the influence of those that tweet about those corporations.

3 Research Methodology

3.1 Sample

The sample of this study is S&P 1500 companies in 2012. We eliminate all financial services companies (one-digit SIC code 6, 306 companies) leaving 1,194 companies for our analyses. The size and industry distribution of our sample is given in Table 1 Panel A and Panel B. Table 1 Panel B shows that, in our sample, there are 405, 308, and 481 companies based on the S&P large-, mid-, and small-cap classification, respectively. In addition, about 50% of our sample is from the manufacturing industry (one-digit SIC code 2 and 3) as given in Table Panel B.

(Insert Table 1 about here)

The unit of analysis is the types of disclosures that SEC registrants are required to report on selected events to the Commission, under Form 8-K. The scope of these events is clearly delineated within the appropriate SEC rule (see Appendix A for a list of types of 8-K filings). The rule defines 31 types of disclosures in nine sections, ranging from “Registrant’s Business and Operations” to “Financial Statements and Exhibits.” For example, Wal-Mart Stores, Inc. discloses information of its election of directors under Item 5.07 Submission of Matters to a Vote of Security Holders in its 8-K filing dated June 4, 2012. We categorize each disclosure type into ten broader categories for our analyses (see Table 1 Panel C), that broadly align with the disclosure classes in the SEC’s rule.

We collect all 8-K filings for the 2012 calendar year from the SEC’s EDGAR database. In a limited number of cases, we concatenate multiple filings that are made on the same day. After elimination of duplicates, there are 11,146 observations remaining for our analyses. We analyze the text in the filing and identify all the above-mentioned disclosure types. Note that it is possible to have multiple types of disclosures in the same 8-K filing. As shown in Table 1 Panel C, the top three most popular types of disclosures are Regulation FD Disclosures, Results of Operations and Financial Condition, and Departure/Election of Directors or Principal Officers.

3.2 Econometric Models

We use Equation (1) to test the relation between Twitter activities and market reactions to 8-K filings. Equation (1) is estimated by using the ordinary least square (OLS) method after controlling for industry fixed effects and company-clustered standard errors.

$$MARKETREACTION_{it} = \beta_0 + \beta_1 EVENT_{it} + \beta_2 TWEET_{it} + \beta_3 EVENT_{it} * TWEET_{it} + \sum Controls_{it} \qquad (1)$$

where $MARKETREACTION_{it}$ can be either *CAR* or *CAV* for company *i* at time *t* (see Appendix B for a summary of variable definitions). The former is the absolute value of the difference between a company’s cumulative equal-weighted market return during the three-day 8-K filing period (i.e., three days centered on the filing date, one day prior to the event date through one day after the filing date and the cumulative return during the window). The cumulative abnormal returns are calculated by using the market model. In particular, we estimate $R_{it}=\beta_0+\beta_1 R_{mt}+\varepsilon_{it}$, where R_{it} is company *i*'s return at time *t*. R_{mt} is the market return, which is the CRSP equally weighted index, at time *t*. We estimate the coefficients by using the ordinary least square (OLS) method in a 255-day periods ending at 45 days before the filing day. The abnormal returns (*AR*) are the differences between actual and expected returns. We then use the mean cumulative abnormal returns to capture the market reactions to 8-K filings, which is the summation of abnormal returns in the 3-day window around the filing date.[2] The latter is the event period market-adjusted share turnover minus the pre-period market-adjusted turnover, where turnover is the average daily dollar volume deflated by the market capitalization. That is, we calculate *CAV* by the sum of the daily trading volume divided by the daily market capitalization in the three day window divided by the average of the daily trading volume divided by the daily market capitalization in a 255 day period prior to the 8-K filing date.

EVENT is 8-K filings at the aggregate level and at the disaggregate level (i.e., different categories or types of 8-K filings). In particular, at the aggregate level, we consider the number of disclosures in the 8-K filings (denoted as *NFILINGS*). At the disaggregate level, we use nine dummy variables to capture different categories or types of 8-K filing items. *MDA* equals one if the 8-K filing has the element about material definitive agreement, and zero otherwise. If the 8-K filing has the element about delisting and bankruptcy, *DLB* equals one and zero otherwise. If the 8-K filing has the information about acquisition and disposition of assets, *ADA* equals one and zero otherwise. *OPS* equal one captures whether the 8-K filing has the information about results of operations and financial condition, and zero otherwise. *OBL* equals one if the 8-K filing has the element about off-balance sheet financial obligation, and zero otherwise. *OFR* equals one if the 8-K filing has the element about departure/election of directors or

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2 In the analyses presented in the paper, we only focus on filing dates. As a robustness test, we also perform our analyses based on effective dates and our results remain similar.

principal officers, and zero otherwise. If the 8-K filing is about amendments to articles of incorporation or bylaws, *BYL* equals one and zero otherwise. *RFD* equals one if the 8-K filing has the element about Regulation FD disclosures, and zero otherwise. STE equals one if the 8-K filing has the information about financial statements and exhibits, and zero otherwise.

TWEET represents various metrics about Twitter activities, which will be elaborated in the next sub-section. *EVENT * TWEET* is the interaction term that captures how Twitter activities would moderate the association between 8-K filings and market reactions.

Controls is a vector of control variables that have typically been shown in prior literature as related to market reactions to 8-K filings in the stock price reaction model and the volume reaction model. We first consider the size of the company (denoted as *SIZE*). *SIZE* is the natural logarithm of a company's total assets at the end of the quarter of the 8-K filing. We also control for sales growth (*SGROWTH*) and earnings volatility (*VOLATILITY*). *SGROWTH* is calculated as the sales revenue at the quarter of the 8-K filing minus the sales revenue in the prior quarter divided by the sales revenue at the quarter of the 8-K filing while *VOLATILITY* is the standard deviation of 16 quarters' net incomes of the company starting from the quarter prior to that of the 8-K filing. We further take into account *LEVERAGE* and *DEBT* in different models. *LEVERAGE* is the company's total liability divided by the total assets at the end of the quarter of the 8-K filing and *DEBT* is total debt divided by total assets at the end of the quarter of the 8-K filing. Finally, the market-to-book ratio (*MB*) and the number of analysts following the company at the end of the quarter of the 8-K filing (*NUMEST*) are considered in the stock price reaction model. Market-to-book ratio is calculated by the stock price times the number of outstanding shares at the end of the quarter divided by the common stock holders' equity at the end of the quarter of the 8-K filing.

3.3 Twitter Metrics

The study leverages the Twitter metrics generated by Topsy Inc., a specialist provider of Twitter analytics. The Topsy database, Topsy Analytics, includes all tweets made on all subjects for the period under study. Users of the Topsy database can query on subject matter; date and time, and geography. We collect all relevant information from Topsy Analytics for all sampled companies by searching for "StockTwit"[3,4] for the 2012 calendar year. By doing so, we are able to gather daily data for the searches. This is a code widely used in communications that involve investment in listed companies. In Topsy Analytics, there are various temporal summary measures about Twitter activities that span the time period covered by the query. The most important metrics are: (1) the number of tweets; (2) the sentiment level, and (3) the influence level of the tweeter. The sentiment level captures the negative or positive tone of the tweet, which ranges from 1 (negative sentiment) to 100 (positive sentiment). The influence score in the Topsy database measures how likely an individual's tweets would get attention from others by using an undisclosed but similar to Google's PageRank algorithm. An influencer's tweets would then, by definition, draw more attention and possibly affect others' decisions. Based on these three important metrics, we calculate three measures that capture Twitter activities for our analyses.

1. Abnormal mention (denoted as *ABMEN*): Abnormal mention is used to capture the relative Twitter activities in terms of the tweeting level in the three-day window around 8-K filing dates compared to the non-event window activities. Following prior literature, we calculate the average tweet volume in a 69-day window (the base window) that ends one day prior to the company's filing of 8-K to the SEC. We then calculate the average tweet volume level for a three-day window around the event day (i.e., one day before and one day after the 8-K filing day plus the filing date). The abnormal measure is calculated by dividing the event window activity (3 days) over the base window activity (69 days). However, note that, prior literature normally calculates the base and event windows on trading days only. Tweets, different from other stock market activities, continue on all days. Accordingly, in our main analyses this measure is calculated by using the number of calendar days.

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3 The StockTwit was developed in 2008 as a simple tag for information distribution on the Web and social media (StockTwits 2014). StockTwits are made up of the ticker symbol, with a '$' prefix (e.g., $AAPL). Some of the tweets using the StockTwit folksonomy originate from users registered on the StockTwits.com website, who link their StockTwits and Twitter accounts.

4 We also search for the names of companies. However, this search does not result in a meaningful sample.

2. Abnormal Sentiment (*ABSENT*): Abnormal sentiment captures the relative tone in the tweets in the three-day window around 8-K filing dates compared to the non-event window tones in the tweets. We calculate the abnormal sentiment by first averaging the sentiment of the tweets in a 69-day window (the base window) that ends one day prior to the company's filing of 8-K to the SEC. We then calculate the average sentiment level for a three-day window around the event day (i.e., one day before and one day after the 8-K filing day plus the filing date). The abnormal measure is calculated by dividing the event window sentiment (3 days) over the base window sentiment (69 days). Similar to *ABMEN*, in our main analyses, this measure is calculated by using the number of calendar days instead of trading days to reflect the uniqueness of tweeting activities.
3. Centrality (*CENTRALITY*): We use the centrality measure to capture the relative importance of companies in the tweeting network, which may have different impact on how Twitter activity affect the association between 8-K filings and the corresponding market reactions. Using the StockTwits in each of the message of a company, we build a network of companies that were connected through the tweets with the eigenvector centrality measure in network analysis. The eigenvector centrality measure has been commonly used as a comprehensive measure of centrality in non-directed graphs. In our context, the vertices are the companies in our sample and the edges are the StockTwits. To do so, we use the algorithm developed by Hirotaka Miura for Stata. This measure is further weighted by the influence level of the tweeters in the year in order to take into account not only the popularity or size of a company in tweets but also the importance of the tweeter.

4 Empirical Results

4.1 Descriptive Statistics

The descriptive statistics of our variables are shown in Table 2. There are four sets of variables: Twitter variables, 8-K variables, stock market reaction variables, and control variables. First, for 8-K variables, Table 2 shows that, the value of *NFILINGS* shows that, on average, there are about two pieces of disclosures in the 8-K filing. The rest of the 8-K variables are dummy variables indicating the categories of 8-K elements, where the mean value suggests the percentage of observations that equal one. The categories with the highest percentage are *STE* (financial statements and exhibits), *OPS* (results of operations and financial condition) and *OFR* (departure/election of directors or principal officers).

(Insert Table 2 about here)

Second, for Twitter variables, there are about 32% more tweets in the 3-day window around 8-K filing dates compared to the base window tweeting activities (the mean value of *ABMEN* is 0.315). These descriptive statistics indicate strong reaction by tweeters to the 8-K filings. For abnormal sentiment, Table 2 demonstrates that, on average, the sentiment score is 0.7% higher (i.e., more positive) in the 3-day event window compared to that in the base window (the mean value of *ABSENT* is 0.007).

Third, the centrality measure of network influence had a mean (median) value of 0.08 (0.04) with standard deviation of 0.11. Figure 1, below, shows the relation between company size (measured as total assets after natural logarithm transformation) and centrality. Although many of the companies have a lower value of centrality weighted by influential tweeters, the figure demonstrates a dispersed distribution especially for mid-sized companies. In addition, larger companies, such as General Electric (ticker symbol GE) or AT&T (ticker symbol T), may have a smaller value of centrality compared to other companies, such as Apple (ticker symbol AAPL), Amazon (ticker symbol AMZN) or Chipotle (ticker symbol CMG), due to the impact of influential tweeters.

(Insert Figure 1 about here)

Fourth, as mentioned earlier, we consider two different stock market reactions: *CAR* and *CAV*. The cumulative abnormal return is 1.246, on average, and the cumulative abnormal trading volume is

0.001, on average, suggesting market reactions to 8-K filings in terms of both price and volume reactions. Last, the companies in our sample, on average, have total assets of about 8 billion dollars after natural logarithm transformation (*SIZE*) with a sales growth rate (*SGROWTH*) of about 2.5%, on average. In addition, the liability to total assets ratio (*LEVERAGE*) is about 53%, on average. Our sample companies, on average, have a market-to-book ratio (*MB*) of about 3 and have about 11 analysts following the companies (*NUMEST*).The Pearson correlations of our variables are given in Table 3. Table 3 shows that *ABMEN* and *ABSENT* are positively related to *CAR* and *CAV*. In addition, we observe correlations larger than 0.5 for *CENTRALITY* and *SGROWTH* as well as *MB* and *NUMEST*. In the additional test section, we further validate our results by taking into account this potential issue and our results remain similar.

(Insert Table 3 about here)

4.2 Results for Trading Volume Reactions

In Equation (1), when the dependent variable is trading volume reactions (*CAV*), the results are given in Table 4. Panels A, B, and C of Table 4 present the findings for *ABMEN*, *ABSENT*, and *CENTRALITY*, respectively. Panel D consider all three Twitter activity variables (*ABMEN*, *ABSENT*, and *CENTRALITY*) and the interactions among them. The first three panels have seven models. Model (1) only focuses on the Twitter activity variables (i.e., *ABMEN*, *ABSENT*, and *CENTRALITY*). Model (2) and Model (3), in addition to Twitter activities, includes 8-K types aggregately and disaggregately. Model (4), Model (5), Model (6), and Model (7) examine the moderating effects of Twitter activities and the association between 8-K types and trading volume reactions. The last panel has eight models. Model (1) includes all three Twitter activity variables but without interaction terms. Model (2) through Model (8) are similar to the seven models in the first three panels but with the interaction terms among *ABMEN*, *ABSENT*, and *CENTRALITY*.

(Insert Table 4 about here)

Table 4 Panel A shows that, first, abnormal mention (*ABMEN*) is consistently positively associated with the trading volume reaction (*CAV*) ($p < 0.01$), suggesting that the relative tweeting activities around the 8-K filing dates would help market participants form/update beliefs towards the filed 8-K information. Such belief update would in turn result in a trading volume change. In addition, Model (2) shows that the disclosures in 8-K filings are also positively related to the trading volume reaction (*CAV*) (the coefficient of *NFILINGS* is 0.063, $p < 0.01$). That is, different categories of 8-K disclosures should affect market participants' beliefs. However, which type of 8-K disclosures would be more significant? This is answered by investigating this effect disaggregately as in Model (3) through Model (7). This positive effect is resulted from the positive association from material definitive agreement (*MDA*) ($p < 0.01$), the negative association from off-balance sheet financial obligations (*OBL*) ($p < 0.05$), and the positive relation from Regulation FD disclosures (*RFD*) ($p < 0.01$). The entry into a material definitive agreement and the disclosure of Regulation FD would be positively related to trading volume as the former provides further information of material agreements not made in "ordinary course of business"[5] while the latter shows that the company complies with the disclosure requirements of Regulation Fair Disclosure. Differently, the off-balance sheet financial obligation is related to direct financial obligations, such as long-term debt or leasing arrangements, of the company. The market interpretation of these events are consistently negative, which would reduce the abnormal trading volume.

We introduce interaction terms in Model (4) through Model (7). The term *ABMEN*CAR* represents the moderating effects of abnormal mentions on the overall corporate information contained in the cumulative abnormal returns. *ABMEN*OPS* represents the moderating effects of abnormal mentions on the 8-Ks providing operational and financial condition information. *ABMEN*OBL* represents the moderating effects of abnormal mentions on the 8-Ks providing off-balance sheet financial obligation

[5] http://investor.gov/news-alerts/investor-bulletins/how-read-8-k

information. While *CAR* represents overall corporate information, *OPS* and *OBL* represent performance information and risk related information, respectively.

The interaction terms demonstrate that there is an negative moderating effect of *ABMEN* on the association between *OBL* and abnormal trading volume (*CAV*) (the coefficients are -0.240 and -0.273, $p < 0.05$), suggesting that relative tweeting activities around the 8-K filing dates would potentially help disseminate the 8-K information and dampen the negative association between the disclosure of off-balance sheet financial obligations and the trading volume reactions. However, we can only observe such moderating effect for the negative information of *OBL* but not for *MDA* and *RFD*.

We next change our focus to abnormal sentiment (*ABSENT*) as given in Table 4 Panel B. Similarly to those in Table 4 Panel A, we observe a positive association between *ABSENT* as well as between the type of 8-K filings (*NFILINGS*) and abnormal trading volume (*CAV*) ($p < 0.01$). This finding again suggests that the relative sentiment (i.e., more positive or more negative) would be important in forming or updating market participants' beliefs of 8-K filing information, which results in abnormal trading volume. In addition, we consistently observe a positive association from material definitive agreement (*MDA*) ($p < 0.01$), the negative association from off-balance sheet financial obligations (*OBL*) ($p < 0.05$), and the positive relation from Regulation FD disclosures (*RFD*) ($p < 0.01$) in addition to a positive coefficient for results of operations and financial conditions (*OPS*) and financial statements and exhibits (*STE*). The interaction terms in Model (4) through Model (7) show that abnormal sentiment (*ABSENT*) around 8-K filing dates can positively moderate the association between concurrent stock price reactions (*CAR*) and abnormal trading volume. This suggests that the relative sentiment (i.e., more negative or more positive) magnifies the impact of concurrent stock price reactions on abnormal trading volume reactions to 8-K filings.

Table 4 Panel C investigates how *CENTRALITY* is related to the trading volume reactions to 8-K filings. Similar to the results of other Twitter activities, we observe a positive association between *CENTRALITY* as well as between the type of 8-K filings (*NFILINGS*) and abnormal trading volume (*CAV*) ($p < 0.01$). This finding suggests that the importance of a company in the tweeting network (after considering the influence levels of tweeters) can significantly affect the dissemination of information, which in turn would change the beliefs of market participants and their subsequent trading volume. We also observe similar association between 8-K types and abnormal trading volume as in Table 4 Panel B. However, differently, we do not observe any moderating effect of *CENTRALITY* on the association between concurrent stock price reaction or disclosure types and abnormal trading volume.

The above three panels fail to take into account the possible interactions among the Twitter activity variables. That is, it is possible that around the 8-K filing dates, abnormal tweeting activities (*ABMEN*), abnormal sentiment (*ABSENT*), and the importance of a company in the tweeting network (*CENTRALITY*) can affect each other's relations to trading volume reactions to 8-K filings. The results are given in Table 4 Panel D. The first model in Table 4 Panel D includes *ABMEN*, *ABSENT*, and *CENTRALITY* but without the interaction terms. Model (1) shows that *ABMEN* and *CENTRALITY* are both positively associated with abnormal trading volume (the coefficients are 0.713, $p < 0.01$, and 0.399, $p < 0.05$, respectively). However, different from the results in Table 4 Panel B, *ABSENT* becomes insignificantly negative, which may result from the interaction effects of these Twitter activity variables. Accordingly, we re-perform our analyses in Panel A, Panel B, and Panel C by including not only *ABMEN*, *ABSENT*, and *CENTRLITY* but also the interactions terms *ABMEN*CENTRALITY*, *ABSENT*CENTRALITY*, *ABMEN*ABSENT*, and *ABMEN*ABSENT*CENTRALITY* in Model (2) through Model (8). First, Model (2) through Model (8) consistently demonstrate a positive association between ABMEN and CAV ($p < 0.01$) as well as CENTRALITY and CAV ($p < 0.01$) which are consistent with the results earlier. Nevertheless, *ABSENT* is negatively related to *CAV* ($p < 0.01$). This finding seems to be inconsistent at the first glance. The two-way interactions demonstrate additional moderating effects among these variables though we do not observe any three-way interactions (i.e., the coefficients of *ABMEN*ABSENT*CENTRALITY* are insignificant). In particular, the abnormal tweeting activities (*ABMEN*) around 8-K filing dates can significantly and positively moderate the negative association between *ABSENT* and *CAV* but significantly and negatively affect the positive association between *CENTRALITY* and *CAV*. In addition, *ABSENT* is positively related to the association between

CENTRALITY and *CAV*. Taken the main effect and the moderating effects together, *ABMEN*, *ABSENT*, and *CENTRALITY* are all positively related to *CAV*. That is, the formation or update of beliefs of a company around 8-K filing dates does not solely rely on abnormal tweeting activities, but also depends on the relative sentiment and the importance of a company in the tweeting network after adjusting for the influential level of the tweeters. Such formation or update of beliefs later increase the abnormal trading volume around 8-K filing dates.

Furthermore, after considering the moderating effects of Twitter activities, similar to those in Panel A and B, we still observe the moderating effect of (1) abnormal sentiment (*ABSENT*) on the association between results of operations and financial conditions (*OPS*) and *CAV*, and (2) abnormal tweeting activities (*ABMEN*) on the relation between off-balance sheet financial obligations (*OBL*) and *CAV*. We also observe some weak evidence regarding how the abnormal sentiment would negatively affect the relation between *OPS* and *CAV* as well as the association between *OBL* and *CAV*.

In summary, our findings demonstrate that Twitter activities are related to the beliefs of investors regarding 8-K filings and in turn affect trading volume reactions to 8-Ks. In addition, Twitter activities not only moderate each other's effect on the trading volume reactions to 8-K filings but also moderate concurrent stock price reactions as well as different types of 8-Ks effect on the trading volume reactions to 8-Ks.

4.3 Results for Stock Price Reactions

In Equation (1), when the dependent variable is the absolute value of stock price reactions (*CAR*), the results are given in Table 5. Similarly, there are four panels in Table 5 and each of the first panels gives the results for *ABMEN*, *ABSENT*, and *CENTRALITY* respectively. Panel D presents the results for the interactions among *ABMEN*, *ABSENT*, and *CENTRALITY*. Panel A, Panel B, and Panel C have six models that focus on only the Twitter activity variables (i.e., *ABMEN*, *ABSENT*, and *CENTRALITY*), different types of 8-K filing disclosures, and the moderating effects of Twitter activities and the association between 8-K types and stock price reactions. In addition to those presented in Panel A, B, and

C, Panel D further considers the interactions among *ABMEN*, *ABSENT*, and *CENTRALITY* in seven models.

(Insert Table 5 about here)

Table 5 Panel A consistently shows that abnormal mention (*ABMEN*) is positively associated with the absolute value of stock price reactions (*CAR*) ($p < 0.01$). That is, the relative tweeting activities can possibly improve the dissemination of information, which increase the stock price reaction. It is also possible that the companies with different relative tweeting activities are those with more active traders, which would reflect in stronger stock price reactions to 8-K filings. In addition, the types of 8-K filing disclosures are also positively related to stock prices reactions (the coefficient of *NFILINGS* is 0.001, $p < 0.05$). When we focus on the interaction terms of *ABMEN***OPS* and *ABMEN***OBL*, Table 5 Panel A shows that abnormal mention (*ABMEN*) can magnify the association between results of operations and financial conditions (*OPS*) and stock price reactions (0.007, $p < 0.01$). Differently, abnormal mention (*ABMEN*) negatively moderates the association between off-balance sheet financial obligations (*OBL*) and stock price reactions (-0.008, $p < 0.05$; -0.006, $p <0.10$). These findings suggest that the abnormal tweeting behavior can magnify the both positive and negative relation between 8-K type disclosures and stock price reactions.

Table 5 Panel B's focus is on abnormal sentiment (*ABSENT*). The results in Panel B consistently demonstrate that abnormal sentiment (*ABSENT*) is positively associated with the absolute value of stock price reactions (*CAR*) ($p < 0.01$). Such finding suggests that the abnormal sentiment of the tweets around 8-K filing dates would show how the tone of this additional information would magnify the stock price reactions to 8-K filings. Though we observe significant positive association between *OPS* and *CAR* as well as significant relation between *OBL* and *CAR*, the moderating effects of *ABSENT* on *OPS* and *OBL* are insignificant.

Table 5 Panel C presents the results for *CENTRALITY*. Similar to the results of *ABMEN* and *ABSENT*, we observe a positive association between *CENTRALITY* and *CAR*, suggesting the importance of a company in the tweeting network (after considering the influence level of tweeter) can magnify the market reactions to 8-K filings. However, we do not observe any moderating effect of *CENTRALITY* on the association between categories of 8-K disclosures on stock price reactions.

Last, we change our focus to the possible interactions among *ABMEN*, *ABSENT*, and *CENTRALITY*. As mentioned earlier, around the 8-K filing dates, it is possible that abnormal tweeting activities (*ABMEN*), abnormal sentiment (*ABSENT*), and the importance of a company in the tweeting network (*CENTRALITY*) can moderate other Twitter variables' relations to stock price reactions to 8-K filings. The findings are presented in Table 5 Panel D. First, Model (1) includes all three Twitter activity variables without considering the interactions. The finding shows that *ABMEN* and *CENTRALITY* are significantly and positively related to the absolute value of stock price reactions (*CAR*) (0.024 and 0.030, $p < 0.01$) but *ABSENT* is insignificant. The interactions terms, *ABMEN*CENTRALITY*, *ABSENT*CENTRALITY*, *ABMEN*ABSENT*, and *ABMEN*ABSENT*CENTRALITY*, in Model (2) through Model (7) further help us understand interrelated roles played by Twitter activities. Specifically, in Model (2) through Model (7), *ABMEN* and *CENTRALITY* are consistently positively related to the absolute value of stock price reactions (*CAR*) ($p < 0.01$) while *ABSENT* is significantly and negatively associated with *CAR* ($p < 0.01$). The two-way interaction terms provide further explanations on the observed associations in Table 5 Panel A, B, and C. That is, the abnormal tweeting activities (*ABMEN*) around 8-K filing dates can significantly and positively moderate the negative association between *ABSENT* and *CAR* but are significantly and negatively related to the positive association between *CENTRALITY* and *CAR*. In addition, *ABSENT* can positively moderate the association between *CENTRALITY* and *CAR*. Though we do not observe any three-way interaction effect (i.e., the coefficients of *ABMEN*ABSENT*CENTRALITY* are insignificant), when we consider both the main effect and two-way interaction effects, *ABMEN*, *ABSENT*, and *CENTRALITY* are all positively related to *CAR*. Taken together, each of the abnormal tweeting activity (*ABMEN*), the abnormal sentiment level (*ABSENT*), or the importance of a company in the tweeting network after considering the importance of the tweeters (*CENTRALITY*) itself is not a single factor the results in stock price reactions to 8-K filings. Instead, these activities interactively indicate the availability of information or how active the traders are in the information environment, which result in stronger stock price reactions to 8-K filings around the filing dates.

Furthermore, after considering the interactions among *ABMEN*, *ABSENT*, and *CENTRALITY*, similar to those demonstrated in Table 5 Panel A and Panel B, we observe (1) an interaction effect of ABMEN on the association between results of operations and financial condition (*OPS*) and *CAR*, and (2) the moderating effect of *ABMEN* on the relation between off-balance sheet financial obligation (*OBL*) and *CAR*. In addition, Table 5 Panel D demonstrate that ABSENT can negatively moderate the association between *OPS* and *CAR*, though weakly ($p < 0.10$) and positively moderate the relation between *OBL* and *CAR* ($p < 0.01$). The additional findings suggest that the relative sentiment level of tweets around the 8-K filing dates can alter the trading activities of market participants given the 8-K information. Table 5 Panel D also shows that the importance of a company in the tweeting network weighted by the importance of tweeters (*CENTRALITY*) can negatively affect the relation between *OPS* and *CAR*. That is, if the company plays a more important role in the tweeting network as weighted by the influence of the tweeters, the effect of *OPS* on *CAR* around 8-K filing dates is smaller, which may result from the availability of credible information on these companies.

In summary, our results suggest that Twitter activities are related to market participants' interests and attention to 8-K filings, which in turn affect stock price reactions to 8-Ks. In addition, we observe the moderating effect of Twitter activities themselves and different types of 8-Ks on the stock price reactions to 8-K filings.

5 Conclusions

The widespread growth in social media supported by Web 2.0 technologies has changed the way individuals interact on the Internet in a wide variety of settings. While there is a plethora of social media technologies (Facebook, Pinterest, Tumblr etc.), Twitter has become particularly influential in communicating time-sensitive information to large and small audiences, with 0.5b tweets and retweets per day made by 0.3b active users. Factors that support the widespread adoption of Twitter are the limited number of characters in each tweet, unrestricted ability to create Tweeters (including robots), open dialog and ubiquitous availability of Twitter clients on essentially every computing platform, including smartphones and tablets. As Twitter users "follow" other users in a public fashion, we can directly observe the nature and strengths of social network connections between tweeters. This allows us to understand the influence levels of tweeters – not all tweeters have equal importance in the social network. Further, the creation of user-generated "hash tags" as a type of folksonomy, enables accurate tracking of areas of interest in tweets, notwithstanding the considerable number of tweets each day.

While the influence of Twitter is well known in communication about news events, consumer products, sports, politics, media and popular culture, it has also been widely adopted for discussion by capital market participants. In particular, the widespread adoption of the StockTwit folksonomy, based on the ticker symbol, has facilitated interaction on listed securities. Scrutinizing tweets that include StockTwits allow us to make previously unavailable insights into the communication between networks of market participants around significant events in the life of corporations. In this study, we concentrate on 8-K filings of significant and material events made by corporations to the SEC. The SEC has developed a clear taxonomy of event types, facilitating analysis of different classes of events. None of these events are known in advance by market participants in the same way as are earnings announcements. The latter class of announcements normally hews to a tightly defined earnings calendar. Further, the news content of the earnings announcement is heralded by analyst forecasts. Study of social media communication around 8-K announcements gives, then, a particularly sharp focus on the market effects of those communications.

The research identifies the more than 11,000 discrete announcements made by commercial and industrial members of the S&P1500 market index. Using the StockTwit folksonomy, and relying on the proprietary database provided by Topsy.com, we identify the daily volume in 2012 of twitter traffic that relate to each S&P1500 constituent. We also identify the aggregate level of sentiment expressed in those daily tweets. This allows us to build models of abnormal tweet volume and sentiment in short windows around the event date, as compared with a base window. Further, Topsy.com identifies the influence level of the top tweeters and their tweets about each of these S&P1500 constituents. As a result we measure the network influence levels (centrality) of communication about each index constituent.

We first measure whether Twitter users tweeting about these corporations react to 8-K announcements. We find that there is a strong reaction to 8-K announcement. On average, we observe that tweet activity within a short window around the announcement is 31.5% higher as compared with a 69 day window preceding the announcement (abnormal tweets). There is also an observable positive change in the level of sentiment in those tweets (abnormal tweets). We then test whether these abnormal tweet volumes and sentiment levels are associated with market volume and price reactions to the 8-K announcement. We also test whether the place of the constituent in the network of tweet flows is associated with market effects. We control for both the class of 8-K event and for a variety of company-level characteristics that have previously been found to be allied with market effects. We find that, tweet activity, sentiment level and network centrality are each associated with both price and volume market effects. These findings are robust to different model formulations including bringing each of these twitter variables of interest into the analysis individually or collectively.

This research contributes to the small but growing literature on the effect of social media on knowledge flows amongst a network of market participants and intermediaries. Our study is differentiated from this literature in the following significant ways. First, we explicitly measure the abnormal level of tweet activity and sentiment, rather than the absolute level. Second, we take into account the relative position of corporations in the social network comprised of tweeters that command varying levels of influence. Third, we investigate the influence of Twitter activity around a variety of significant and material events. We find that Twitter activity is associated with market effects across a range of different classes of events, ranging from the corporation entering into agreements with third parties to new off-balance sheet commitments. Likewise, we conclude that the market attention and market behavior reflected in tweets in the announcement period do cause significant market activity. In other words, the level and nature of market attention a corporate announcement receives determines the level of price and volume movements of stocks in the capital markets. This suggests that further investigations of tweets and tweeter features can allow us to empirically understand the intricacies of market and investor behavior that was previously a realm of experimental research.

The research is subject to limitations. First, we do not definitely know that the tweets are directly associated with the 8-K announcements. Some tweets will flow as an indirect result of the announcement to the SEC. Future research should investigate the extent of direct association between the tweet and announcement and whether such an association adds additional power to our empirical analysis. Second, our measure of network influence (centrality) is drawn from the most influential tweets across the complete year of the study. Future research should attempt to measure network influence in time periods more closely aligned with the announcement to the SEC. Third, we only investigate Twitter activity. We do not bring into the study measures of other types of social media. Other studies could investigate the relative importance of Twitter, Facebook, and blogs.

References

Merton, R. 1987. A simple model of capital market equilibrium with incomplete information. *Journal of Finance* 42 (3): 483-510.

XXXX (Forthcoming), Twitter-based dissemination of corporate disclosure and capital market: evidence from Australian listed companies, *Journal of Information Systems*.

Bamber, L., and Y. S. Cheon. 1995. Differential price and volume reactions to accounting earnings announcements. *The Accounting Review* 70 (3):417-441.

Beaver, W. 1968. The information content of annual earnings announcements. *Journal of Accounting Research* 9:67-92.

Blankespoor, E., G. S. Miller, and H. D. White. 2014. The role of dissemination in market liquidity: Evidence from firms' use of Twitter. *The Accounting Review* 89 (1):79-112.

Bollen, J., M. Huina, and Z. Xiaojun. 2011. Twitter mood predicts the stock market. *Journal of Computational Science* 2 (1):1-8.

Bonner, S. E. 2008. *Judgment and Decision Making in Accounting*. Upper Saddle River, NJ: Prentice Hall.

Botosan, C. A. 1997. Disclosure level and the cost of equity capital. *Accounting Review* 72 (3):323-349.

Brown, S., S. A. Hillegeist, and K. Lo. 2004. Conference calls and information asymmetry. *Journal of Accounting and Economics* 37 (3):343-366.

Bushee, B. J., D. A. Matsumoto, and G. S. Miller. 2003. Open versus closed conference calls: the determinants and effects of broadening access to disclosure. *Journal of Accounting and Economics* 34:149-180.

Cha, M., H. Haddadi, F. Benevenuto, and K. P. Gummadi. 2010. Measuring User Influence in Twitter: The Million Follower Fallacy. In *Fourth International AAAI Conference on Weblogs and Social Medi*. Washington, DC: Association for the Advancement of Artificial Intelligence.

Clarkson, P. M., J. L. Kao, and G. D. Richardson. 1994. The voluntary inclusion of forecasts in the MD&A section of annual reports. *Contemporary Accounting Research* 11 (1):423-450.

Curtis, A., V. J. Richardson, and R. Schmardebeck. 2014. *Investor Attention and the Pricing of Earnings News*. SSRN, July 16 2014 [cited October 15 2014]. Available from http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2467243.

Dietrich, J. R., S. J. Kachelmeier, D. N. Kleinmuntz, and T. J. LInsmeier. 2001. Market Efficiency, Bounded Rationality and Supplemental Business Reporting Disclosures. *Journal of Accounting Research* 39 (2):243-268.

Du, H., and W. Jiang. 2014. Does Social Media Matter? Initial Empirical Evidence. *Journal of Information Systems* 29:forthcoming.

Elliott, W. B., F. D. Hodge, and L. M. Sedor. 2012. Using Online Video to Announce a Restatement: Influences on Investment Decisions and the Mediating Role of Trust. *The Accounting Review* 87 (2):513-535.

Francis, J., D. Nanda, and P. E. R. Olsson. 2008. Voluntary Disclosure, Earnings Quality, and Cost of Capital. *Journal of Accounting Research* 46 (1):53-99.

Frankel, R., M. Johnson, and D. J. Skinner. 1999. An empirical examination of conference calls as a voluntary disclosure medium. *Journal of Accounting Research* 37 (1):133-150.

Huang, A. H., A. Y. Zang, and R. Zheng. 2014. Evidence on the Information Content of Text in Analyst Reports. *Accounting Review* 89 (6):2151–2180.

Jackson, M. O. 2010. *Social and Economic Networks*. Princeton, NJ: Princeton University Press.

Jansen, B. J., M. Zhang, K. Sobel, and A. Chowdury. 2009. Twitter power: Tweets as electronic word of mouth. *Journal of the American Society for Information Science and Technology* 60 (11):2169-2188.

Kadushin, C. 2011. *Understanding Social Networks: Theories, Concepts, and Findings*. Oxford: Oxford University Press.

Kim, E., Y. Sung, and H. Kang. 2014. Brand followers' retweeting behavior on Twitter: How brand relationships influence brand electronic word-of-mouth. *Computers in Human Behavior* 37:18-25.

Kim, O., and R. Verrecchia. 1991. Trading volume and price reactions to public announcements. *Journal of Accounting Research* 29 (2):302-321.

Kimbrough, M. D., and I. Y. Wang. 2014. Are Seemingly Self-Serving Attributions in Earnings Press Releases Plausible? Empirical Evidence. *The Accounting Review* 89 (2):635-667.

Kothari, S. P. 2001. Capital markets research in accounting. *Journal of Accounting and Economics* 31 (1-3):105-231.

Lerman, A., and J. Livnat. 2010. The new Form 8-K disclosures. *Review of Accounting Studies* 15:752-778.

Miller, J. S., and L. M. Sedor. 2013. Do Stock Prices Influence Analysts' Earnings Forecasts? *Behavioral Research in Accounting* 26 (1):85-108.

Nagy, J., and A. Midha. 2014. The Value of Earned Audiences: How Social Interactions Amplify TV Impact. *Journal of Advertising Research* 54 (4):448-453.

Pak, A., and P. Paroubek. 2010. Twitter as a corpus for sentiment analysis and opinion mining, 2010.

Rui, H., Y. Liu, and A. Whinston. 2013. Whose and what chatter matters? The effect of tweets on movie sales. *Decision Support Systems* 55 (4):863-870.

Scott, J. 2013. *Social Network Analysis*. Thousand Oaks, CA: Sage Publications.

SEC. 2004. *Final Rule: Additional Form 8-K Disclosure Requirements and Acceleration of Filing Date*. Securities and Exchange Commission, 18 March 2004 2004 [cited 31 December 2004]. Available from http://www.sec.gov/rules/final/33-8400.htm#seciv.

———. 2014. *SEC Says Social Media OK for Company Announcements if Investors Are Alerted*. Securities and Exchange Commission 2013 [cited October 20 2014]. Available from http://www.sec.gov/News/PressRelease/Detail/PressRelease/1365171513574.

StockTwits. 2014. *About StockTwits*. StockTwits, Inc. 2014 [cited October 20 2014]. Available from http://stocktwits.com/about.

Sul, H., A. R. Dennis, and L. I. Yuan. 2014. Trading on Twitter: The Financial Information Content of Emotion in Social Media. In *Hawaii International Conference on Systems Science*. Hawaii. HI: University of Hawaii, 806-815.

Twitter. 2014. *Twitter Reports Third Quarter 2014 Results*. Twitter, Inc., October 27 2014 [cited December 1 2014]. Available from http://goo.gl/oEAN99.

Twitter.com. 2014. *About Twitter*. Twitter.com 2014 [cited October 20 2014]. Available from https://about.twitter.com/.

Zhou, M., L. Lei, J. Wang, W. Fan, and A. G. Wang. 2014, Forthcoming. Social Media Adoption and Corporate Disclosure. *Journal of Information Systems* 29.

Appendix A. List of 8-K Filings (http://www.sec.gov/answers/form8k.htm)

Section 1 Registrant's Business and Operations

- Item 1.01 Entry into a Material Definitive Agreement
- Item 1.02 Termination of a Material Definitive Agreement
- Item 1.03 Bankruptcy or Receivership
- Item 1.04 Mine Safety - Reporting of Shutdowns and Patterns of Violations

Section 2 Financial Information

- Item 2.01 Completion of Acquisition or Disposition of Assets
- Item 2.02 Results of Operations and Financial Condition
- Item 2.03 Creation of a Direct Financial Obligation or an Obligation under an Off-Balance Sheet Arrangement of a Registrant
- Item 2.04 Triggering Events That Accelerate or Increase a Direct Financial Obligation or an Obligation under an Off-Balance Sheet Arrangement
- Item 2.05 Costs Associated with Exit or Disposal Activities
- Item 2.06 Material Impairments

Section 3 Securities and Trading Markets

- Item 3.01 Notice of Delisting or Failure to Satisfy a Continued Listing Rule or Standard; Transfer of Listing
- Item 3.02 Unregistered Sales of Equity Securities
- Item 3.03 Material Modification to Rights of Security Holders

Section 4 Matters Related to Accountants and Financial Statements

- Item 4.01 Changes in Registrant's Certifying Accountant
- Item 4.02 Non-Reliance on Previously Issued Financial Statements or a Related Audit Report or Completed Interim Review

Section 5 Corporate Governance and Management

- Item 5.01 Changes in Control of Registrant
- Item 5.02 Departure of Directors or Certain Officers; Election of Directors; Appointment of Certain Officers; Compensatory Arrangements of Certain Officers
- Item 5.03 Amendments to Articles of Incorporation or Bylaws; Change in Fiscal Year
- Item 5.04 Temporary Suspension of Trading Under Registrant's Employee Benefit Plans
- Item 5.05 Amendment to Registrant's Code of Ethics, or Waiver of a Provision of the Code of Ethics
- Item 5.06 Change in Shell Company Status
- Item 5.07 Submission of Matters to a Vote of Security Holders
- Item 5.08 Shareholder Director Nominations

Section 6 Asset-Backed Securities

- Item 6.01 ABS Informational and Computational Material
- Item 6.02 Change of Servicer or Trustee
- Item 6.03 Change in Credit Enhancement or Other External Support
- Item 6.04 Failure to Make a Required Distribution
- Item 6.05 Securities Act Updating Disclosure

Section 7 Regulation FD

- Item 7.01 Regulation FD Disclosure

Section 8 Other Events

- Item 8.01 Other Events (The registrant can use this Item to report events that are not specifically called for by Form 8-K, that the registrant considers to be of importance to security holders.)

Section 9 Financial Statements and Exhibits

- Item 9.01 Financial Statements and Exhibits

Appendix B. Variable Definitions

Variable	Definition	Data Source
Twitter Variables		
ABMEN	Abnormal mention, which is calculated as follows. We first calculate the average tweet volume in a 69-day window (the base window) that ends one day prior to the company's filing of 8-K to the SEC. We then calculate the average tweet volume level for a three-day window around the event day (i.e., one day before and one day after the 8-K filing day plus the filing date). The abnormal measure is calculated by dividing the event window activity (3 days) over the base window activity (69 days). In our main analyses, these days are calendar days to reflect the unique characteristic of tweeting activities.	Topsy
ABSENT	Abnormal sentiment, which is calculated by first averaging the sentiment of the tweets in a 69-day window (the base window) that ends one day prior to the company's filing of 8-K to the SEC. We then calculate the average sentiment level for a three-day window around the event day (i.e., one day before and one day after the 8-K filing day plus the filing date). The abnormal measure is calculated by dividing the event window sentiment (3 days) over the base window sentiment (69 days). In our main analyses, these days are calendar days to reflect the unique characteristic of tweeting activities.	Topsy
CENTRALITY	Centrality measure that captures how important a company in the tweeting network. To do so, we use the StockTwits in each of the message of a company and build a network of companies that are connected through the tweets with the eigenvector centrality measure by using the algorithm developed by Hirotaka Miura for Stata. In the network, the vertices were the companies in our sample and the edges were the StockTwits. This measure was weighted by the number of influential tweeters for each company in the year of 2012.	Topsy
8-K Filings and Types		
NFILINGS	Number of categories or types of disclosures in the 8-K filings in the sample period.	8-K filings
MDA	Dummy variable, if the 8-K filing has the element about material definitive agreement, *MDA* equals one and zero otherwise.	8-K filings
DLB	Dummy variable, if the 8-K filing has the element about delisting and bankruptcy, *DLB* equals one and zero otherwise.	8-K filings
ADA	Dummy variable, if the 8-K filing has the element about acquisition and disposition of assets, *ADA* equals one and zero otherwise.	8-K filings
OPS	Dummy variable, if the 8-K filing has the element about results of operations and financial condition, *OPS* equals one and zero otherwise.	8-K filings
OBL	Dummy variable, if the 8-K filing has the element about off-balance sheet financial obligation, *OBL* equals one and zero otherwise.	8-K filings

OFR	Dummy variable, if the 8-K filing has the element about departure/election of directors or principal officers, *OFR* equals one and zero otherwise.	8-K filings
BYL	Dummy variable, if the 8-K filing has the element about amendments to articles of incorporation or bylaws, *BYL* equals one and zero otherwise.	8-K filings
RFD	Dummy variable, if the 8-K filing has the element about Regulation FD disclosures, *RFD* equals one and zero otherwise.	8-K filings
STE	Dummy variable, if the 8-K filing has the element about financial statements and exhibits, *STE* equals one and zero otherwise.	8-K filings
Stock Market Reaction Variables		
CAV	Cumulative abnormal trading volume in the three day window around 8-K filing dates, which is the event period market-adjusted share turnover minus the pre-period market-adjusted turnover, where turnover is the average daily dollar volume deflated by the market capitalization. Specifically, cumulative abnormal trading volume is calculated by the sum of the daily trading volume divided by the daily market capitalization in the three day window divided by the average of the daily trading volume divided by the daily market capitalization in a 255 day period prior to the 8-K filing date.	CRSP
CAR	Cumulative abnormal returns in the three day window around 8-K filing dates. The cumulative abnormal returns are calculated by using the market model. That is, we first regress the companies' return on the market return in the 255 day window. Then we sum the differences between actual and predicted company return in the three day window. In particular, we estimate $R_{it}=\beta_0+\beta_1 R_{mt}+\varepsilon_{it}$, where R_{it} is company *i*'s return at time *t*. R_{mt} is the market return, which is the CRSP equally weighted index, at time *t*. We estimate the coefficients by using the ordinary least square (OLS) method in a 255-day periods ending at 45 days before the filing day. The abnormal returns (*AR*) are the differences between actual and expected returns. We then use the mean cumulative abnormal returns to capture the market reactions to 8-K filings, which is the summation of abnormal returns in the 3-day window around the filing date. In our analyses, we use the absolute value of *CAR*.	CRSP
Control Variables		
SIZE	Size of the company, which is the natural logarithm of a company's total assets at the end of the quarter when the 8-K filings occur.	Compustat
SGROWTH	Sales growth of the company at the end of the quarter when the 8-K filings occur. Sales growth equals sales revenue at time *t* (the quarter when the 8-K filing occurs) minus sales revenue at time *t*-1 divided by sales revenue at time *t*-1.	Compustat

VOLATILITY	Volatility of the company's quarterly net income, which equals the standard deviation of 16 quarters' net incomes of the company before the quarter when the 8-K filings occur (i.e., time *t*-1 to time *t*-16)	Compustat
LEVERAGE	Leverage ratio of the company, which is the company's total liability divided by the total assets at the end of the quarter when the 8-K filings occur.	Compustat
MB	Market-to-book ratio, which is calculated by the stock price times the number of outstanding shares at the end of the quarter divided by the common stock holders' equity at the end of the quarter when the 8-K filings occur.	Compustat
DEBT	Debt to asset ratio, which equals total debt divided by total assets at the end of the quarter when the 8-K filings occur.	Compustat
NUMEST	The number of analysts following the company at the end of the quarter when the 8-K filings occur.	I/B/E/S

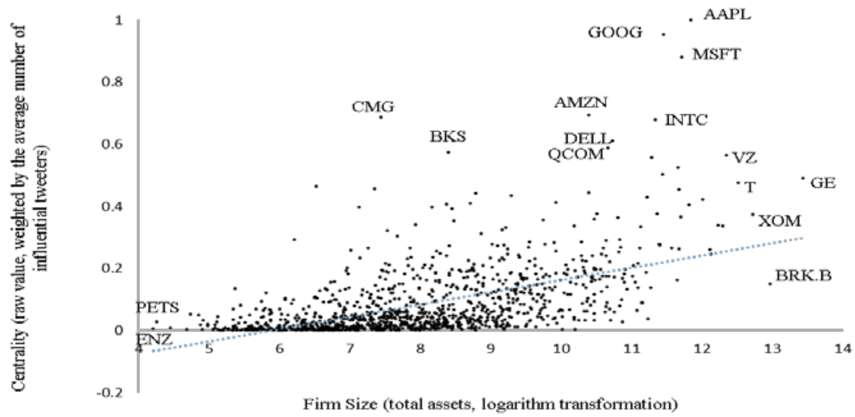

Figure 1. Company Size and Centrality

Table 1. Sample Composition

Panel A. S&P Market-Cap Classification

S&P Market-Cap Classification	Number of Companies	Percentage
Large	405	33.92
Mid	308	25.80
Small	481	40.28
Total	1,194	100.00

Panel B. Industry Breakdown

Industry (1-digit SIC code)	Description	Number of Companies	%
0	Agriculture, Forestry, and Fishing	3	0.25
1	Mining and Construction	89	7.45
2	Manufacturing	210	17.59
3	Manufacturing	380	31.83
4	Transportation, Communications, Electric, Gas, and Sanitary Services	139	11.64
5	Whole Sale and Retail Trade	156	13.07
7	Services	159	13.32
8	Services	55	4.61
9	Public Administration	3	0.25
Total		1,194	100.00

See https://www.osha.gov/pls/imis/sic_manual.html for details of the SIC code

Panel C. 8-K Categories

8-K Category	Number of Observations§
Material Definitive Agreement	1,545
Delisting and Bankruptcy	68
Acquisition and Disposition of Assets	380
Results of Operations and Financial Condition	3,090
Off-Balance Sheet Financial Obligation	763
Departure/Election of Directors or Principal Officers	2,660
Amendments to Articles of Incorporation or Bylaws	414
Financial Statements and Exhibits	2,083
Regulation FD Disclosures	8,172
Other Events	3,735

§ There can be multiple disclosure items per 8-K filings.

Table 2. Descriptive Statistics

Variable	N	Mean	Std. Dev.	Quartiles		
				Q1	Q2	Q3
Twitter Variables						
ABMEN	9,587	0.315	0.743	-0.195	0.223	0.727
ABSENT	9,587	0.007	0.146	-0.053	0.000	0.091
CENTRALITY	11,046	0.064	0.100	0.008	0.024	0.085
8-K Variables						
NFILINGS	11,146	2.055	0.855	2.000	2.000	2.000
MDA	11,146	0.139	0.346	0.000	0.000	0.000
DLB	11,146	0.006	0.078	0.000	0.000	0.000
ADA	11,146	0.034	0.181	0.000	0.000	0.000
OPS	11,146	0.277	0.448	0.000	0.000	1.000
OBL	11,146	0.068	0.253	0.000	0.000	0.000
OFR	11,146	0.239	0.426	0.000	0.000	0.000
BYL	11,146	0.037	0.189	0.000	0.000	0.000
RFD	11,146	0.187	0.390	0.000	0.000	0.000
STE	11,146	0.733	0.442	0.000	1.000	1.000
Stock Market Reaction Variables						
CAV	10,944	0.001	0.053	-0.019	0.001	0.020
CAR	10,945	1.246	1.190	0.704	0.972	1.423
Control Variables						
SIZE	11,146	8.040	1.572	6.846	7.920	9.133
SGROWTH	11,146	0.025	0.287	-0.054	0.009	0.076
VOLATILITY	11,146	39.968	126.805	3.454	9.327	29.534
LEVERAGE	11,146	0.529	0.213	0.381	0.531	0.678
MB	11,145	2.988	34.096	1.346	2.010	3.183
DEBT	11,029	0.233	0.179	0.095	0.224	0.343
NUMEST	11,073	11.452	7.741	5.000	10.000	16.000

Table 3. Pearson Correlations

	1	2	3	4	5	6	7	8	9	10	11	12	13
1	1.000												
2	0.138*	1.000											
3	0.063*	-0.001	1.000										
4	0.138*	0.031*	-0.047*	1.000									
5	0.194*	0.022*	-0.056*	0.671*	1.000								
6	0.427*	0.034*	-0.006	0.109*	0.114*	1.000							
7	0.063*	0.172*	0.014	0.013	0.005	-0.027*	1.000						
8	-0.004	-0.026*	0.575*	-0.010	-0.028*	-0.078*	0.005	1.000					
9	0.006	0.002	-0.022*	0.004	0.010	0.004	0.008	-0.012	1.000				
10	0.019	0.013	0.460*	-0.022*	-0.028*	-0.026*	0.007	0.429*	-0.016	1.000			
11	-0.040*	-0.015	0.087*	0.021*	0.003	-0.018	-0.004	0.448*	-0.015	0.109*	1.000		
12	-0.024*	-0.003	0.023*	0.013	0.012	-0.028*	-0.014	0.029*	-0.003	0.010	0.017	1.000	
13	-0.050*	-0.011	0.029*	0.038*	0.017	-0.033*	-0.001	0.385*	0.001	0.062*	0.785*	0.012	1.000

* $p < 0.05$

1. *ABMEN*, 2. *ABSENT*, 3. *CENTRALITY*, 4. *NFILINGS*, 5. *CAV*, 6. *CAR*, 7. *SIZE*, 8. *SGROWTH*, 9. *VOLATILITY*, 10. *LEVERAGE*, 11. *MB*, 12. *DEBT*, 13. *NUMEST*

Table 4. Main Results for Trading Volume Reactions
Panel A. Abnormal Mention

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)
Intercept	1.472***	1.351***	1.398***	1.395***	1.397***	1.404***	1.400***
	(9.36)	(8.72)	(9.11)	(8.84)	(8.88)	(9.27)	(8.76)
ABMEN	0.711***	0.701***	0.696***	0.697***	0.722***	0.708***	0.742***
	(19.05)	(19.15)	(14.16)	(14.11)	(10.76)	(13.72)	(10.34)
NFILINGS		0.063***					
		(3.92)					
MDA			0.227***	0.223***	0.224***	0.227***	0.221***
			(2.87)	(2.94)	(2.89)	(2.88)	(2.95)
DLB			0.101	0.0941	0.101	0.109	0.103
			(0.89)	(0.83)	(0.88)	(0.96)	(0.90)
ADA			-0.002	-0.001	-0.002	0.004	0.006
			(-0.05)	(-0.02)	(-0.05)	(0.08)	(0.12)
OPS			0.0576	0.0544	0.109***	0.0515	0.108***
			(1.10)	(1.05)	(2.64)	(0.97)	(2.87)
OBL			-0.165**	-0.165**	-0.160**	-0.160**	-0.153**
			(-2.40)	(-2.42)	(-2.40)	(-2.38)	(-2.38)
OFR			0.010	0.007	0.011	0.012	0.012
			(0.26)	(0.21)	(0.29)	(0.33)	(0.33)
BYL			0.098	0.095	0.097	0.103	0.100
			(1.43)	(1.43)	(1.42)	(1.50)	(1.50)
RFD			0.133***	0.132***	0.130***	0.136***	0.132***
			(2.76)	(2.75)	(2.71)	(2.81)	(2.76)
STE			0.013	0.014	0.011	0.010	0.010
			(0.48)	(0.56)	(0.40)	(0.40)	(0.37)
*ABMEN*CAR*				0.817			0.811
				(0.59)			(0.59)
*ABMEN*OPS*					-0.079		-0.094
					(-1.07)		(-1.22)
*ABMEN*OBL*						-0.240**	-0.273**
						(-2.02)	(-2.14)
CAR	-1.086	-1.096	-1.136	-2.139*	-1.143	-1.133	-2.136*
	(-1.29)	(-1.30)	(-1.37)	(-1.89)	(-1.38)	(-1.37)	(-1.90)
SIZE	-0.074***	-0.074***	-0.074***	-0.073***	-0.071***	-0.075***	-0.072***
	(-4.81)	(-4.82)	(-4.77)	(-4.61)	(-4.82)	(-4.82)	(-4.71)
SGROWTH	0.010	0.010	0.011	0.011	0.010	0.012	0.013
	(0.32)	(0.32)	(0.34)	(0.35)	(0.33)	(0.40)	(0.41)
VOLATILITY	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.41)	(0.52)	(0.63)	(0.59)	(0.54)	(0.65)	(0.50)
LEVERAGE	0.244**	0.231**	0.228**	0.225**	0.224**	0.230**	0.224**
	(2.45)	(2.34)	(2.35)	(2.31)	(2.34)	(2.38)	(2.31)
N	9,397	9,397	9,397	9,397	9,397	9,397	9,397
adj. R^2	0.191	0.192	0.194	0.196	0.195	0.195	0.197

t statistics in parentheses
* $p < .1$, ** $p < .05$, *** $p < .01$

Panel B. Abnormal Sentiment

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)
Intercept	1.789***	1.504***	1.363***	1.353***	1.357***	1.363***	1.356***
	(6.44)	(5.72)	(5.34)	(5.43)	(5.29)	(5.34)	(5.45)
ABSENT	0.308**	0.283**	0.266**	0.359**	0.310**	0.268**	0.354**
	(2.40)	(2.22)	(2.12)	(2.58)	(2.25)	(2.03)	(2.27)
NFILINGS		0.144***					
		(7.55)					
MDA			0.290***	0.287***	0.290***	0.290***	0.287***
			(3.28)	(3.22)	(3.28)	(3.28)	(3.23)
DLB			0.102	0.099	0.102	0.102	0.010
			(0.97)	(0.97)	(0.98)	(0.97)	(0.98)
ADA			0.007	0.014	0.007	0.008	0.015
			(0.13)	(0.25)	(0.12)	(0.14)	(0.28)
OPS			0.583***	0.541***	0.585***	0.583***	0.541***
			(16.39)	(15.55)	(16.44)	(16.40)	(15.71)
OBL			-0.308***	-0.300***	-0.308***	-0.308***	-0.299***
			(-3.80)	(-3.68)	(-3.80)	(-3.79)	(-3.67)
OFR			-0.015	-0.013	-0.015	-0.015	-0.012
			(-0.37)	(-0.32)	(-0.36)	(-0.37)	(-0.32)
BYL			0.078	0.078	0.077	0.078	0.078
			(1.04)	(1.09)	(1.03)	(1.04)	(1.10)
RFD			0.166***	0.162***	0.166***	0.166***	0.162***
			(3.22)	(3.10)	(3.22)	(3.22)	(3.11)
STE			0.068**	0.065**	0.067**	0.068**	0.065**
			(2.40)	(2.30)	(2.39)	(2.40)	(2.31)
*ABSENT*CAR*				18.030***			18.080***
				(3.18)			(3.19)
*ABSENT*OPS*					-0.172		0.059
					(-0.79)		(0.30)
*ABSENT*OBL*						-0.037	-0.155
						(-0.17)	(-0.68)
CAR	-0.615	-0.647	-0.641	-1.274	-0.612	-0.642	-1.289
	(-0.61)	(-0.65)	(-0.66)	(-1.37)	(-0.62)	(-0.66)	(-1.36)
SIZE	-0.065***	-0.065***	-0.057***	-0.056***	-0.057***	-0.057***	-0.056***
	(-4.13)	(-4.16)	(-3.68)	(-3.58)	(-3.68)	(-3.69)	(-3.58)
SGROWTH	0.020	0.020	0.046	0.038	0.047	0.046	0.038
	(0.55)	(0.54)	(1.30)	(1.00)	(1.32)	(1.30)	(1.00)
VOLATILITY	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(1.04)	(1.27)	(1.09)	(1.03)	(1.08)	(1.09)	(1.03)
LEVERAGE	0.148	0.122	0.169*	0.172*	0.168*	0.169*	0.173*
	(1.43)	(1.20)	(1.72)	(1.77)	(1.71)	(1.72)	(1.77)
N	9,397	9,397	9,397	9,397	9,397	9,397	9,397
adj. R^2	0.007	0.017	0.059	0.076	0.059	0.058	0.076

t statistics in parentheses
* $p < .1$, ** $p < .05$, *** $p < .01$

Panel C. Centrality

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)
Intercept	1.958***	1.678***	1.548***	1.540***	1.556***	1.549***	1.549***
	(6.92)	(6.39)	(6.08)	(6.07)	(6.09)	(6.08)	(6.08)
CENTRALITY	0.814***	0.902***	0.873***	0.836***	0.810***	0.873***	0.764***
	(4.23)	(4.66)	(4.48)	(4.68)	(4.18)	(4.42)	(4.41)
NFILINGS		0.153***					
		(8.95)					
MDA			0.291***	0.290***	0.290***	0.291***	0.289***
			(3.61)	(3.58)	(3.60)	(3.61)	(3.58)
DLB			0.102	0.106	0.104	0.102	0.109
			(1.01)	(1.04)	(1.03)	(1.01)	(1.06)
ADA			-0.012	-0.012	-0.013	-0.012	-0.013
			(-0.24)	(-0.25)	(-0.25)	(-0.24)	(-0.26)
OPS			0.576***	0.576***	0.560***	0.576***	0.558***
			(17.94)	(17.94)	(15.59)	(17.94)	(15.38)
OBL			-0.303***	-0.302***	-0.303***	-0.303***	-0.307***
			(-4.06)	(-4.05)	(-4.06)	(-3.86)	(-3.88)
OFR			-0.025	-0.024	-0.024	-0.025	-0.023
			(-0.69)	(-0.66)	(-0.67)	(-0.69)	(-0.65)
BYL			0.056	0.058	0.057	0.056	0.058
			(0.83)	(0.85)	(0.84)	(0.83)	(0.86)
RFD			0.162***	0.163***	0.163***	0.162***	0.164***
			(3.57)	(3.60)	(3.58)	(3.56)	(3.61)
STE			0.085***	0.085***	0.086***	0.085***	0.086***
			(3.31)	(3.32)	(3.32)	(3.31)	(3.33)
*CENTRALITY *CAR*				7.633			7.694
				(0.82)			(0.82)
*CENTRALITY *OPS*					0.263		0.287
					(1.23)		(1.23)
*CENTRALITY *OBL*						0.006	0.089
						(0.01)	(0.22)
CAR	-0.639	-0.671	-0.674	-1.144	-0.674	-0.674	-1.148
	(-0.73)	(-0.77)	(-0.79)	(-1.07)	(-0.79)	(-0.79)	(-1.07)
SIZE	-0.098***	-0.101***	-0.092***	-0.091***	-0.092***	-0.092***	-0.091***
	(-5.45)	(-5.63)	(-5.13)	(-5.13)	(-5.14)	(-5.13)	(-5.14)
SGROWTH	0.021	0.019	0.042	0.043	0.041	0.042	0.042
	(0.76)	(0.68)	(1.60)	(1.64)	(1.58)	(1.60)	(1.62)
VOLATILITY	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(-0.83)	(-0.73)	(-0.79)	(-0.71)	(-0.79)	(-0.79)	(-0.70)
LEVERAGE	0.205**	0.187**	0.232**	0.231**	0.232**	0.232**	0.231**
	(2.11)	(1.96)	(2.51)	(2.50)	(2.51)	(2.50)	(2.50)
N	10,853	10,853	10,853	10,853	10,853	10,853	10,853
adj. R^2	0.009	0.021	0.065	0.066	0.065	0.065	0.066

t statistics in parentheses
* $p < .1$, ** $p < .05$, *** $p < .01$

Panel D. Interactions between *ABMEN*, *ABSENT*, and *CENTRALITY*

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)	Model (8)
Intercept	1.569***	1.550***	1.434***	1.484***	1.447***	1.456***	1.490***	1.438***
	(9.30)	(9.96)	(9.38)	(9.67)	(9.23)	(9.08)	(9.85)	(8.77)
ABMEN	0.713***	0.775***	0.764***	0.761***	0.745***	0.766***	0.776***	0.780***
	(18.87)	(14.94)	(15.01)	(12.28)	(11.17)	(9.00)	(11.96)	(8.39)
ABSENT	-0.174	-0.614***	-0.620***	-0.604***	-0.565***	-0.488***	-0.642***	-0.516***
	(-1.40)	(-4.58)	(-4.65)	(-4.47)	(-3.82)	(-3.09)	(-4.56)	(-3.14)
CENTRALITY	0.399**	0.698***	0.740***	0.755***	0.700***	0.865***	0.741***	0.792***
	(2.21)	(3.62)	(3.81)	(3.93)	(3.41)	(4.68)	(3.83)	(4.09)
*ABMEN*ABSENT*		0.675**	0.676**	0.660**	0.760**	0.769***	0.677**	0.857***
		(2.49)	(2.50)	(2.43)	(2.48)	(2.74)	(2.49)	(2.62)
ABMEN CENTRALITY*		-0.761**	-0.762**	-0.777**	-0.866***	-0.498	-0.788**	-0.638*
		(-2.42)	(-2.43)	(-2.49)	(-3.35)	(-1.09)	(-2.51)	(-1.76)
ABSENT CENTRALITY*		1.647*	1.649*	1.523*	1.491*	1.383*	1.571*	1.459*
		(1.89)	(1.90)	(1.77)	(1.83)	(1.65)	(1.83)	(1.84)
*ABMEN*ABSENT* CENTRALITY*		-0.768	-0.759	-0.729	-1.878	-0.519	-0.754	-1.683
		(-0.34)	(-0.34)	(-0.32)	(-1.36)	(-0.25)	(-0.34)	(-1.25)
NFILINGS			0.066***					
			(4.10)					
MDA				0.225***	0.225***	0.221***	0.226***	0.222***
				(2.84)	(2.92)	(2.85)	(2.85)	(2.92)
DLB				0.079	0.080	0.072	0.084	0.081
				(0.69)	(0.71)	(0.63)	(0.73)	(0.72)
ADA				0.019	0.021	0.017	0.024	0.025
				(0.37)	(0.40)	(0.34)	(0.46)	(0.49)
OPS				0.057	0.057	0.146***	0.050	0.155***
				(1.10)	(1.13)	(3.10)	(0.94)	(3.74)
OBL				-0.158**	-0.159**	-0.151**	-0.179**	-0.161**
				(-2.31)	(-2.32)	(-2.26)	(-2.55)	(-2.32)
OFR				0.008	0.010	0.008	0.010	0.014
				(0.21)	(0.29)	(0.22)	(0.28)	(0.39)
BYL				0.104	0.106	0.0981	0.109	0.105
				(1.51)	(1.61)	(1.43)	(1.58)	(1.60)
RFD				0.133***	0.134***	0.127***	0.137***	0.130***
				(2.74)	(2.77)	(2.62)	(2.79)	(2.67)
STE				0.019	0.020	0.015	0.017	0.013
				(0.72)	(0.77)	(0.57)	(0.64)	(0.51)
*ABMEN*CAR*					0.052			0.032
					(0.03)			(0.02)
*ABSENT*CAR*					8.813*			8.734*
					(1.74)			(1.74)
*CENTRALITY*CAR*					9.383			8.251
					(0.83)			(0.77)
*ABMEN*OPS*						-0.0583		-0.102
						(-0.73)		(-1.28)
*ABSENT*OPS*						-0.650**		-0.466*
						(-2.24)		(-1.93)
*CENTRALITY*OPS*						-0.882		-0.690
						(-1.36)		(-1.38)
*ABMEN*OBL*							-0.258**	-0.276**
							(-2.19)	(-2.12)

ABSENT OBL*							0.456**	0.335
							(2.29)	(1.59)
CENTRALITY OBL*							0.430	0.286
							(1.05)	(0.71)
CAR	-1.019	-1.270	-1.280	-1.312	-2.220**	-1.281	-1.307	-2.111**
	(-1.16)	(-1.43)	(-1.44)	(-1.50)	(-2.06)	(-1.47)	(-1.49)	(-2.04)
SIZE	-0.090***	-0.089***	-0.090***	-0.090***	-0.086***	-0.088***	-0.092***	-0.084***
	(-4.61)	(-4.56)	(-4.64)	(-4.66)	(-4.17)	(-4.58)	(-4.69)	(-4.09)
SGROWTH	0.012	0.011	0.011	0.011	0.010	0.016	0.013	0.015
	(0.40)	(0.35)	(0.37)	(0.37)	(0.33)	(0.56)	(0.42)	(0.52)
VOLATILITY	-0.000	-0.000	-0.000	-0.000	0.000	-0.000	-0.000	-0.000
	(-0.41)	(-0.38)	(-0.34)	(-0.20)	(0.13)	(-0.35)	(-0.13)	(-0.06)
LEVERAGE	0.278***	0.275***	0.265**	0.263**	0.255**	0.261**	0.262**	0.254**
	(2.63)	(2.61)	(2.54)	(2.57)	(2.44)	(2.56)	(2.56)	(2.43)
N	9,319	9,319	9,319	9,319	9,319	9,319	9,319	9,319
adj. R^2	0.190	0.197	0.199	0.201	0.206	0.203	0.202	0.209

Table 5. Main Results for Stock Price Reactions
Panel A. Abnormal Mention

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
Intercept	0.051^{***}	0.049^{***}	0.045^{***}	0.045^{***}	0.045^{***}	0.045^{***}
	(14.15)	(12.82)	(12.58)	(11.14)	(12.42)	(11.08)
ABMEN	0.024^{***}	0.024^{***}	0.020^{***}	0.018^{***}	0.020^{***}	0.018^{***}
	(24.26)	(24.11)	(17.08)	(12.69)	(16.81)	(12.18)
NFILINGS		0.001^{**}				
		(2.23)				
MDA			0.002	0.002	0.002	0.002
			(1.19)	(1.30)	(1.21)	(1.31)
DLB			0.007	0.007	0.007	0.007
			(1.16)	(1.17)	(1.21)	(1.20)
ADA			-0.001	-0.001	-0.001	-0.001
			(-0.74)	(-0.76)	(-0.61)	(-0.67)
OPS			0.013^{***}	0.009^{***}	0.013^{***}	0.009^{***}
			(8.81)	(5.20)	(8.54)	(5.28)
OBL			-0.001	-0.002	-0.001	-0.002
			(-0.95)	(-1.26)	(-0.86)	(-1.19)
OFR			0.000	0.000	0.000	0.000
			(0.24)	(0.14)	(0.34)	(0.22)
BYL			-0.001	-0.001	-0.001	-0.001
			(-0.43)	(-0.38)	(-0.34)	(-0.32)
RFD			0.003^{**}	0.003^{**}	0.003^{**}	0.003^{**}
			(2.01)	(2.24)	(2.09)	(2.29)
STE			-0.000	-0.000	-0.000	-0.000
			(-0.39)	(-0.18)	(-0.48)	(-0.26)
*ABMEN*OPS*				0.007^{***}		0.007^{***}
				(3.03)		(2.77)
*ABMEN*OBL*					-0.008^{**}	-0.006^{*}
					(-2.31)	(-1.65)
SIZE	-0.006^{***}	-0.006^{***}	-0.006^{***}	-0.006^{***}	-0.006^{***}	-0.006^{***}
	(-13.81)	(-13.78)	(-13.34)	(-13.43)	(-13.36)	(-13.43)
MB	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(-0.98)	(-0.99)	(-1.00)	(-1.02)	(-1.00)	(-1.01)
DEBT	0.013^{***}	0.013^{***}	0.013^{***}	0.013^{***}	0.013^{***}	0.013^{***}
	(3.30)	(3.22)	(3.43)	(3.46)	(3.47)	(3.49)
NUMEST	0.000^{***}	0.000^{***}	0.000^{***}	0.000^{***}	0.000^{***}	0.000^{***}
	(4.47)	(4.50)	(4.78)	(4.21)	(4.74)	(4.21)
N	9,240	9,240	9,240	9,240	9,240	9,240
adj. R^2	0.222	0.222	0.237	0.239	0.237	0.240

t statistics in parentheses
* $p < .1$, ** $p < .05$, *** $p < .01$

Panel B. Abnormal Sentiment

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
Intercept	0.063***	0.055***	0.046***	0.046***	0.046***	0.046***
	(15.51)	(13.97)	(12.18)	(12.15)	(12.16)	(12.14)
ABSENT	0.012***	0.012***	0.011***	0.011***	0.010***	0.010***
	(3.31)	(3.16)	(3.15)	(3.63)	(2.79)	(3.10)
NFILINGS		0.004***				
		(7.43)				
MDA			0.004**	0.004**	0.004**	0.004**
			(2.15)	(2.15)	(2.15)	(2.15)
DLB			0.006	0.006	0.006	0.006
			(1.24)	(1.24)	(1.22)	(1.22)
ADA			-0.000	-0.001	-0.001	-0.001
			(-0.36)	(-0.36)	(-0.41)	(-0.41)
OPS			0.028***	0.028***	0.028***	0.028***
			(19.97)	(20.10)	(19.97)	(20.11)
OBL			-0.006***	-0.006***	-0.006***	-0.006***
			(-3.20)	(-3.20)	(-3.28)	(-3.29)
OFR			-0.000	-0.000	-0.000	-0.000
			(-0.32)	(-0.33)	(-0.34)	(-0.34)
BYL			-0.002	-0.002	-0.002	-0.002
			(-0.73)	(-0.73)	(-0.75)	(-0.74)
RFD			0.003**	0.003**	0.003**	0.003**
			(2.53)	(2.53)	(2.53)	(2.53)
STE			0.001	0.001	0.001	0.001
			(1.56)	(1.56)	(1.57)	(1.57)
*ABSENT*OPS*				0.001		0.001
				(0.06)		(0.15)
*ABSENT*OBL*					0.011	0.011
					(1.37)	(1.46)
SIZE	-0.006***	-0.006***	-0.006***	-0.006***	-0.006***	-0.006***
	(-13.54)	(-13.45)	(-12.63)	(-12.62)	(-12.61)	(-12.61)
MB	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(-1.20)	(-1.24)	(-1.19)	(-1.19)	(-1.19)	(-1.19)
DEBT	0.010**	0.008**	0.012***	0.012***	0.012***	0.012***
	(2.31)	(2.04)	(2.95)	(2.95)	(2.95)	(2.95)
NUMEST	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(6.08)	(6.11)	(6.16)	(6.16)	(6.15)	(6.15)
N	9,240	9,240	9,240	9,240	9,240	9,240
adj. R^2	0.048	0.054	0.142	0.142	0.142	0.142

t statistics in parentheses
* $p < .1$, ** $p < .05$, *** $p < .01$

Panel C. Centrality

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
Intercept	0.071***	0.063***	0.054***	0.054***	0.054***	0.054***
	(17.44)	(16.36)	(14.67)	(14.63)	(14.67)	(14.63)
CENTRALITY	0.038***	0.040***	0.038***	0.038***	0.038***	0.038***
	(4.82)	(5.05)	(4.90)	(5.02)	(4.88)	(4.99)
NFILINGS		0.004***				
		(8.87)				
MDA			0.004***	0.004***	0.004***	0.004***
			(2.64)	(2.64)	(2.64)	(2.64)
DLB			0.009	0.009	0.009	0.009
			(1.52)	(1.52)	(1.52)	(1.52)
ADA			-0.001	-0.001	-0.001	-0.001
			(-0.52)	(-0.51)	(-0.51)	(-0.51)
OPS			0.028***	0.028***	0.028***	0.028***
			(21.64)	(19.66)	(21.64)	(19.67)
OBL			-0.006***	-0.006***	-0.006***	-0.006***
			(-3.59)	(-3.59)	(-3.60)	(-3.60)
OFR			-0.000	-0.000	-0.000	-0.000
			(-0.08)	(-0.08)	(-0.08)	(-0.08)
BYL			-0.002	-0.002	-0.002	-0.002
			(-1.04)	(-1.04)	(-1.04)	(-1.04)
RFD			0.004***	0.004***	0.004***	0.004***
			(2.92)	(2.92)	(2.93)	(2.92)
STE			0.002**	0.002**	0.002**	0.002**
			(2.31)	(2.30)	(2.30)	(2.30)
*CENTRALITY *OPS*				-0.001		-0.001
				(-0.13)		(-0.11)
*CENTRALITY *OBL*					0.006	0.006
					(0.46)	(0.43)
SIZE	-0.007***	-0.007***	-0.007***	-0.007***	-0.007***	-0.007***
	(-14.51)	(-14.56)	(-13.60)	(-13.58)	(-13.60)	(-13.58)
MB	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(-1.23)	(-1.27)	(-1.19)	(-1.19)	(-1.19)	(-1.19)
DEBT	0.012***	0.011***	0.015***	0.015***	0.015***	0.015***
	(3.11)	(2.86)	(3.82)	(3.82)	(3.82)	(3.82)
NUMEST	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(3.54)	(3.45)	(3.46)	(3.46)	(3.45)	(3.45)
N	10,675	10,675	10,675	10,675	10,675	10,675
adj. R^2	0.050	0.057	0.144	0.144	0.144	0.144

t statistics in parentheses
* $p < .1$, ** $p < .05$, *** $p < .01$

Panel D. Interactions between *ABMEN*, *ABSENT*, and *CENTRALITY*

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)
Intercept	0.057***	0.056***	0.054***	0.051***	0.049***	0.051***	0.049***
	(13.18)	(12.42)	(11.50)	(11.19)	(9.66)	(10.98)	(9.59)
ABMEN	0.024***	0.026***	0.025***	0.022***	0.019***	0.023***	0.019***
	(23.93)	(21.56)	(21.44)	(16.21)	(11.49)	(16.04)	(11.16)
ABSENT	-0.004	-0.017***	-0.017***	-0.014***	-0.009***	-0.016***	-0.012***
	(-1.35)	(-5.38)	(-5.42)	(-4.62)	(-3.09)	(-5.03)	(-3.66)
CENTRALITY	0.030***	0.040***	0.041***	0.043***	0.047***	0.042***	0.046***
	(4.01)	(5.59)	(5.67)	(5.88)	(6.09)	(5.89)	(6.06)
*ABMEN*ABSENT*		0.019***	0.019***	0.019***	0.019***	0.020***	0.020***
		(3.21)	(3.21)	(3.11)	(3.00)	(3.27)	(3.14)
ABMEN CENTRALITY*		-0.024***	-0.024***	-0.027***	-0.017*	-0.028***	-0.017*
		(-3.40)	(-3.42)	(-3.71)	(-1.73)	(-3.73)	(-1.77)
ABSENT CENTRALITY*		0.051***	0.051***	0.045***	0.035**	0.048***	0.038**
		(3.37)	(3.35)	(2.99)	(2.26)	(3.14)	(2.44)
*ABMEN*ABSENT *CENTRALITY*		-0.042	-0.042	-0.042	-0.025	-0.043	-0.027
		(-1.27)	(-1.26)	(-1.26)	(-0.71)	(-1.29)	(-0.77)
NFILINGS			0.001**				
			(2.54)				
MDA				0.002	0.002	0.002	0.002
				(1.25)	(1.39)	(1.26)	(1.39)
DLB				0.006	0.006	0.006	0.006
				(1.04)	(1.00)	(1.05)	(1.01)
ADA				-0.001	-0.001	-0.001	-0.001
				(-0.43)	(-0.49)	(-0.39)	(-0.47)
OPS				0.014***	0.010***	0.013***	0.010***
				(8.86)	(5.66)	(8.56)	(5.71)
OBL				-0.001	-0.002	-0.002	-0.003
				(-0.80)	(-1.11)	(-1.38)	(-1.64)
OFR				0.000	-0.000	0.000	0.000
				(0.15)	(-0.01)	(0.22)	(0.06)
BYL				-0.001	-0.001	-0.001	-0.001
				(-0.35)	(-0.41)	(-0.29)	(-0.36)
RFD				0.003**	0.003**	0.003**	0.003**
				(2.03)	(2.16)	(2.12)	(2.22)
STE				0.000	0.000	-0.000	0.000
				(0.02)	(0.13)	(-0.06)	(0.05)
*ABMEN*OPS*					0.008***		0.008***
					(3.41)		(3.11)
*ABSENT*OPS*					-0.018*		-0.017*
					(-1.87)		(-1.74)
CENTRALITY OPS*					-0.041***		-0.039***
					(-2.69)		(-2.61)
*ABMEN*OBL*						-0.009***	-0.007*
						(-2.71)	(-1.94)
ABSENT OBL*						0.028***	0.024***
						(3.84)	(3.43)
CENTRALITY OBL*						0.017	0.016
						(1.26)	(1.16)

SIZE	-0.007***	-0.007***	-0.007***	-0.007***	-0.007***	-0.007***	-0.007***
	(-13.56)	(-13.53)	(-13.58)	(-13.25)	(-13.07)	(-13.25)	(-13.05)
MB	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(-0.99)	(-1.03)	(-1.04)	(-1.05)	(-1.06)	(-1.05)	(-1.06)
DEBT	0.015***	0.015***	0.015***	0.016***	0.016***	0.016***	0.016***
	(3.87)	(3.88)	(3.81)	(4.02)	(4.01)	(4.06)	(4.04)
NUMEST	0.000**	0.000**	0.000**	0.000**	0.000*	0.000**	0.000*
	(2.07)	(2.04)	(2.02)	(2.24)	(1.79)	(2.17)	(1.76)
N	9,162	9,162	9,162	9,162	9,162	9,162	9,162
adj. R^2	0.223	0.227	0.227	0.242	0.246	0.243	0.246