Is Firms' Social Media Engagement Informative about Firm Performance?

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Abstract

In this paper, I examine whether the volume of a firm's followers' engagement is informative to capital market participants. I define engagement as the collective response – likes, retweets, and replies – of the followers to the firm's tweets. My data comprises of 46,090 Tweet firm-quarters, and approximately 343 million engagement actions (likes, retweets, and replies) of the firms' followers collected from the Primary Twitter sites of 2,197 publicly-traded US firms between 2006 and 2017. I find that changes in engagement volume represent value-relevant information to investors, and this information gets impounded in the stock prices concurrently. Changes in each component of followers' engagement – likes, retweets, and replies – are also value relevant. Furthermore, the followers' engagement volume is a forward-looking indicator of stock prices, as the monthly change in the engagement volume varies directly with the following month's stock returns. This is an important finding because while extant literature has studied the consequences of the firm's tweets, it has not considered the followers' response. In additional analysis, I find that changes in engagement volume incrementally explain the firm's sales growth, and this may be the source of additional information to the investors. The findings also suggest that the observed results are not driven by investor attention.

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1. Introduction

In recent times, a growing number of firms have started using social media to disseminate information and communicate directly with their stakeholders. Twitter, in particular, has emerged as the most popular social media platform for the dissemination of information by firms.[1] Jung et al. (2018) show that almost 50% of S&P 1500 firms have a presence on Twitter. Twitter provides a unique platform for dissemination because it facilitates real-time two-way communication and feedback between a firm and its followers while limiting the size of the message.[2] Firms use Twitter to disseminate information and to engage directly with all their stakeholders (e.g., customers, investors, suppliers, employees). Recent accounting literature aims to understand why and how firms use Twitter. Most of this literature focuses on tweets, which are typically dissemination of information already released on other media platforms. The aggregate response of the followers, on the other hand, is *new information* because it represents real-time feedback of the followers to these firm-initiated tweets,[3] which is the focus of my paper.

In this paper, I study whether social media interactions between firms and their followers provide relevant information about firm performance.[4] Specifically, I examine whether a change in the volume of the followers' engagement with firm-initiated tweets is informative to capital market participants or random noise.[5] Additionally, I test whether this engagement behavior of a firm's followers predicts the firm's sales growth. I use a comprehensive sample of approximately 17.9 million firm-initiated tweets, and 184 million

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[1] Jung et al. (2018) report that 47% and 42% of the S&P 1500 firms use Twitter and Facebook, respectively as of January, 2013.

[2] A Twitter account has followers who follow and respond to the information being disseminated on that account. Followers can show their interest to a particular tweet by liking, retweeting, or replying. It is reasonable to assume that followers are persons or entities who are interested in knowing more about and interacting with the owner of the account. However, it is possible to see and respond to tweets without being a follower. Therefore, the number of followers is only a lower bound on the visibility of the Twitter account and its tweets.

[3] I refer to the tweets initiated by a firm on its official Twitter account as firm-initiated tweets.

[4] The number of followers of a Twitter account can be observed in real time. However, one cannot see its past values or the time-trend.

[5] 'Followers' engagement' refers to the engagement of the followers with a firm's tweets.

likes, 126 million retweets, and 33 million replies by followers, from the Primary Twitter sites of 2,197 publicly-traded US firms from 2006 to 2017 for my analysis.[6]

Firms tweet about myriad topics such as sales and marketing, customer fulfillment, financial disclosures, corporate disclosures, new product launches, CSR initiatives, etc. These tweets generate varying levels of interest from the followers; a follower may respond by liking, retweeting, or replying to a particular tweet or may choose to ignore the tweet.[7] I define engagement as the sum of likes, retweets, and replies by the followers to a tweet. The level of engagement with a firm's tweet is the collective response or feedback of the followers to that tweet. Jung et al. (2018) show that firms are more likely to tweet positive news or information. Marketing studies have also shown that firms focus on generating more response or buzz from the followers and adopt new and innovative techniques to leverage social media for stimulating customer engagement and demand (Schniederjans, Cao and Schniedarjans, 2013; Rishika, Kumar, Janakiraman and Bezawada, 2013; Gong, Zhang, Zhao and Jiang, 2017; Lee, Hosanagar and Nair, 2018). Some of the firm-initiated tweets, such as earnings announcements, may be important enough to impact the market on their own. However, there is an almost continuous flow of tweets, the majority of which are not corporate disclosures. Most of these tweets may not be significant enough for investors to take notice. Therefore, it is the combined response of the followers to the firm-initiated tweets over a period, which may be more meaningful. As such, the aggregate engagement during a period can be considered as the 'buzz' about the firm on the internet, reflecting the followers' enthusiasm for the firm's products, services, corporate disclosures, or any other information that the firm disseminates on its Twitter account.[8]

The purpose of this study is to examine whether the overall 'buzz,' measured by a change in the firm's followers' engagement volume is informative to the capital market.[9] On the one hand, the followers'

[6] I define Primary Twitter account as the main official Twitter account. A link for it appears on the webpage of the firm. In addition, the firm may have other Twitter accounts as well. In this study, I consider tweets of Primary Twitter accounts only and, henceforth, refer to them as Primary Twitter accounts or just as Twitter accounts.

[7] See Section 3.2 for more details on engagement and each of its components – like, retweet, and reply.

[8] The 'buzz' could be positive or negative depending on the tone of the tweet, retweet and replies.

[9] For brevity, engagement volume refers to both the volume of engagement as well as the volume of each of the components of engagement (likes, retweets, and replies) wherever used.

engagement level may be no more than a random noise to the information environment of the firm, especially if the followers are not representative of the firm's customer and investor base. Also, followers' engagement can represent either positive or negative feedback as it is not clear whether retweets and replies are manifestations of positive or negative response. On the other hand, the level of engagement to a firm's tweets is the collective feedback indicative of the overall excitement for the firm and its products and services. Therefore, the engagement volume aggregated over a period can convey incremental, value-relevant information about the firm's contemporaneous business performance or its outlook for future periods. If so, such information should get reflected in the stock prices as it is in the public domain. This means that changes in engagement volume should contribute positively to the firm value during the same period. Therefore, ex-ante, it is not clear whether changes in followers' engagement are value-relevant beyond the concurrent information already contained in the other known sources of information such as changes in consensus analyst forecast, the frequency of press releases, newspaper coverage, and voluntary disclosures.

To the extent that the followers' engagement level is informative to the capital market, a second issue is whether such information is fully reflected in the firm value (stock prices) contemporaneously, or whether there is an under- or over-reaction. That is, do changes in followers' engagement or its components predict future stock returns? I use five different measures to proxy for the aggregate information contained in the followers' engagement volume.[10] Using Fama-MacBeth (1973) monthly cross-sectional regressions I test whether a change in the followers' engagement volume is priced by the capital market and whether there's underreaction or overreaction.

The results suggest that changes in the followers' engagement volume are informative to the capital market participants and get impounded in the stock prices concurrently. Therefore, changes in followers' engagement volume are value-relevant and help explain the observed cross-sectional differences in stock

[10] See Section 3.2 for a detailed description of each of these five measures.

returns beyond the priced common risk factors and other public sources of information about the firm. Changes in each component of the followers' engagement – likes, retweets, and replies – are also value relevant. I also find that the capital market underreacts to the information that changes in the followers' engagement volume represents. In particular, results indicate that it takes two months for the capital market to fully impound the engagement information into stock prices.

Marketing studies have shown that firms focus on generating more response or buzz from the followers for stimulating customer engagement and demand. Therefore, the volume of a firm's followers' engagement aggregated over a given period may convey incremental information about the firm's sales and sales growth during that period. However, prior literature also shows that it is inconclusive whether and how tweeting influences product demand and sales. Therefore, ex-ante it is not clear whether the aggregate level of followers' engagement is informative about the sales of the firm during the period. I use OLS multiple linear regression with year-quarter and firm fixed-effects to test whether changes in the followers' engagement predict the firm's sales growth. The results suggest a strong positive association between changes in the followers' engagement volume and the firm's sales growth during the same period, and this could be the source of additional new information to investors.

An alternative explanation for the findings could be that the followers' engagement is not new information, but the buzz it creates may be attracting investor attention. Earnings announcement is the most anticipated event and generates the maximum attention from the investors. Therefore, I repeat the analysis removing the months of earnings announcement to rule out this alternative explanation. I find that changes in followers' engagement are still value relevant and, therefore, must signify new information to the capital market participants.

My study makes significant contributions to four distinct strands of literature. Firstly, it contributes to a growing body of accounting literature that studies social media. One strand of this literature examines the determinants and market consequences of firms disseminating information through their official Twitter accounts (Blankespoor et al., 2014; Lee et al., 2015; Jung et al., 2018; Crowley et al., 2018). Another stream of this literature studies the information content of third-party tweets about firms' earnings, products, or stocks and whether it predicts a firm's future sales and stock returns (Tang 2018; Bartov et al., 2018).[11] Extant literature has also examined specific categories of firms' tweets using event studies (Blankespoor et al., 2014; Lee et al., 2015).[12] However, it is still an unexplored question whether the followers' engagement conveys any new information to the market participants. My study extends this literature by showing that the followers' engagement represents a new value-relevant information source for the investors.

Second, the study contributes to the literature on the efficiency of capital markets; whether it impounds all relevant public information in the stock prices, or there is a significant underreaction or overreaction (Ball and Brown, 1968; Fama 1970; Bernard and Thomas, 1990; Sloan, 1996; Bloomfield, 2002; Hirshleifer et al., 2002; Hirshleifer et al., 2002). I demonstrate that investors find the buzz which the followers' engagement volume represents informative and impound it into stock prices concurrently, though not fully. I also show that this information is forward-looking and helps predict the next month's stock returns too.

My study also adds to the literature on the role of financial and non-financial leading indicators in predicting future earnings and firm value such as market penetration, air pollution index, customer satisfaction scores, order backlog, web traffic and customer ratings (Amir and Lev, 1996; Ittner and Larcker, 1998; Deng et al., 1999; Hughes, 2000; Trueman et al., 2001; Rajgopal et al., 2003; Luo et al., 2013) in firm valuation. My paper highlights another source of nonfinancial information – the volume of followers' engagement with firm-initiated tweets – that could be informative about the firm's future financial performance to investors.

Finally, my paper also contributes to the literature in marketing and information systems which focus on social media and its economic consequences (Schniederjans, et al., 2013; Rishika et al.,2013; Luo

[11] Third- party tweets are between individuals and are not on the official Twitter accounts of firms.
[12] The papers focus on one category of tweets or individual tweets around a specific event and draw their inferences using a small sample of firms.

et al., 2013; Rui et al., 2013; Yu et al., 2013; Gong et al., 2017). I show that a firm's followers' engagement is positively associated with the firm value, stock returns, and sales growth.

The rest of the paper is organized as follows: I discuss Literature review and Hypotheses development in Section 2; Sample, Data collection, Variable Construction and Research Design in Section 3; Descriptive Statistics in Section 4; Empirical Results in Section 5; and finally Conclude with my findings in Section 6.

2. Literature Review and Hypothesis Development

2.1 Literature Review

In the last ten years, social media has emerged as one of the most popular platforms of communication between people. Consequently, an ever-increasing number of firms have started using social media for the dissemination of firm-related information and engaging with investors, customers, employees, and other stakeholders. Twitter,[13] arguably, has emerged as one of the most popular social media platforms. Kang, Hosseini, Savickas, and Singh (2019), hereafter referred to as HKSS, show that close to 52% of publicly-traded US firms have official Twitter accounts as on Dec 31, 2017. This new medium of information dissemination has also generated a great deal of interest from accounting researchers. One strand of literature examines the determinants and market consequences of firms disseminating information on Twitter. Blankespoor, Miller, and White (2014) show that firms can reduce information asymmetry by more broadly disseminating their news using Twitter. Lee, Hutton, and Shu (2015) examine how corporate social media affects the capital market consequences of firms' disclosure of negative news in the context of product recalls. Their results suggest that corporate social media attenuates the negative price reaction to product recall disclosures. Interestingly, their study also indicates that the level of control a firm has over its social media content plays a role in the attenuation benefits. Both these

[13] In its 2017 10-K filing, Twitter disclosed that it had 330 million average monthly active users (MAUs) in the three months ended December 31, 2017.As of Dec. 31,2018 ,new age high-tech firms such as Google and Facebook had approximately 20.5 million and 13.5 million followers, respectively and can tweet information and engage directly with them.

papers demonstrate the vital role of social media, in general, and Twitter, in particular, as a medium of information dissemination by firms, over and above the coverage by the business press.[14]

A recent paper by Jung, Naughton, Tahoun, and Wang (2018) examines whether firms use social media (Twitter) to strategically disseminate financial information. Using a sample of S&P 1500 firms from 2010 to 2013, the paper shows that firms are less likely to use Twitter to propagate quarterly earnings news when the news is bad and when the magnitude of the earnings forecast errors is greater, consistent with strategic use of Twitter. Crowley, Huang, and Lu (2018) study the discretionary dissemination of financial tweets on Twitter around earnings announcements, accounting filings, and other important corporate events by S&P 1500 firms. Their results indicate that firms make discretionary choices in timing and presentation format when disseminating information on Twitter and also incorporate instantaneous feedback from their Twitter account followers into their dissemination strategies.

Another stream of this literature studies the information content of third-party tweets about firms' earnings, products or stocks and whether it predicts a firm's future sales and stock returns(e.g., Bollen et al., 2011; Mao et al., 2012; Curtis et al., 2016; Tang, 2018; Bartov et al. ,2018). These studies use the concept of 'Wisdom of Crowds' to explain the predictive power of third- party-generated tweets.[15] Tang (2018) examines the predictive ability of third-party-generated product information tweets, aggregated at the firm- level, about firm-level sales. The paper finds that the incremental information content of the aggregate information increases with the extent to which the Twitter comments are representative of the broad customer response to products and brands. Bartov, Faurel, and Mohanram (2018) also focus on individual tweets around a firm's earnings announcement and study whether aggregate opinion from

[14] Bushee et al. (2009) find that business press acts as an information intermediary and plays an important role in disseminating information as well as by creating new information. Their study also suggests that business press reduces information asymmetry around earnings announcements, with broader dissemination of information having a bigger impact.

[15] Wisdom of Crowds refers to the aggregation of information provided by many (non-expert) individuals which may often predict outcomes more precisely than experts as the individuals may be coming from diverse backgrounds and are, therefore, less likely to herd.

individual tweets predicts its earnings and announcement returns. They find results consistent with their conjecture after controlling for concurrent information or opinion from traditional media sources.

Most prior accounting studies examining the use of Twitter by firms have focused on firms' tweets. These studies show that firm-initiated tweets are primarily disseminating information that has already been disclosed by the firm on other media platforms and, therefore, do not contain any new information. The aggregate response of the followers, on the other hand, may represent *new information* because it includes real-time feedback of the followers to firm-initiated tweets. As Twitter facilitates two-way communication in real-time, it permits the public to express opinions about the firm, its products, and its actions. As such, the engagement level and content can potentially convey value-relevant information. My study is different from these prior studies because it focuses on the effect of the buzz created by the firm-initiated tweets, and not on the firms' tweets themselves, to predict the firm's stock returns and sales growth. I examine an aspect of firms' communication on Twitter which has not yet been explored, to the best of my knowledge. Furthermore, prior studies use a small sample of firms over a limited time period, in part due to data collection constraints. Such an approach raises concerns about the generalizability of the results. My sample is more representative as it includes all publicly-traded US firms' Twitter accounts and tweets from January 2006 to December 2017.

2.2 Hypothesis Development

When a firm creates a Twitter account, it establishes a fast and reliable method of disseminating news and other information to its stakeholders (customers, investors, distributors, etc.).Twitter also proves a powerful platform where the followers can share their views and opinions with the firm through publicly viewable feedback. For example, the firm may use Twitter to market its products and services or to fulfill a service request from a customer or to make corporate announcements. Twitter, therefore, allows the firm to engage with its stakeholders in a way that traditional modes of communication such as press releases, television, conference calls, etc. do not. When a firm tweets, a follower may respond by liking, retweeting, or replying to the tweet – collectively defined in the paper as engagement. Firms are more likely to tweet positive news (Jung et al., 2018). Studies also show that tweets affect customer behavior (Gong et al. 2017) and that greater consumer participation is also associated with a higher frequency of customer visits (Rishika et al. 2013). Therefore, the level of engagement to a firm's tweet is the collective feedback of the followers to that tweet indicative of the overall 'buzz' or excitement for the firm and its products and services. A high level of stakeholder engagement can represent a high degree of enthusiasm for the firm, such as satisfaction with the firm's products, customer service, an increase in the firm's visibility, and anticipation of the firm's future products. A lower engagement level, on the other hand, may indicate lukewarm enthusiasm. The firm can also compare the engagement level of two different marketing campaigns or product launches. Therefore, the followers' engagement volume or a change in the engagement volume aggregated for a given period can convey incremental information about the firm's business performance during that period.

However, with an open and interactive social media platform, the firm also relinquishes its full control over the contents being transmitted on its official Twitter account (Lee et al., 2015). Therefore, a firm with a Twitter account also becomes vulnerable as any criticism and negative feedback by even a few can be viewed by other followers, investors, and competitors. The firm can still influence what gets communicated and discussed on its Twitter account; however, the followers, now, also exercise a high degree of control through their engagement and feedback process. An online platform such as Twitter is also susceptible to manipulation, rumors or negative sentiment by 'interested' parties (Lee et al., 2018; Lee et al., 2015), and most of the communication is qualitative. Moreover, all firms may not be equally adept at engaging successfully with their customers on social media (Lee et al., 2018), even though they might be performing well otherwise.

Some of the firm-initiated tweets, such as earnings announcements, may be important enough to impact the market on their own. However, there is an almost continuous flow of tweets, the majority of which are not corporate disclosures. Most of these tweets may not be significant enough for investors to take notice. Therefore, it is the combined response of the followers to the firm-initiated tweets over a period, which may be more meaningful. The aggregate information in the followers' engagement and its components (likes, retweets, replies), to the extent that it is not reflected in tweets or other traditional sources of information, can be value-relevant and get impounded in the stock prices (Fama,1970). This implies that the followers' engagement volume can be associated with firm value. Similarly, a change in the engagement volume or its components can be value relevant, and if so, get impounded in the stock prices immediately. On the other hand, the buzz which the followers' engagement represents may merely be adding random noise to the overall information environment of the firm. This will be particularly true if the followers are not representative of the firm's customer and investor base. As explained in greater detail in Section 3.2, likes are positive by definition. But it is not clear whether retweets and replies are manifestations of positive or negative response by the followers. Therefore, followers' engagement can represent either positive or negative feedback. Hence, taken together, it is an open question whether the followers' engagement is informative to the capital market or not. It is also possible that each component of engagement may impact stock prices differently as they represent different ways in which the followers respond to tweets. Therefore, ex-ante, it is unclear whether the aggregate information in the change in followers' engagement or its components will get incorporated in stock prices beyond the concurrent information already contained in the other known sources of information such as press, analyst forecasts, and voluntary disclosures. This leads to the following hypotheses stated in the *NULL FORM*:

Hypothesis 1A: Ceteris Paribus, a change in the followers' engagement volume is not associated with the firm's stock return during a given period.

Hypothesis 1B: Ceteris Paribus, a change in each component (likes, retweets, replies) of the followers' engagement volume is not associated with the firm's stock return during a given period.

Researchers in accounting and finance have also shown that there are notable exceptions to the efficient market hypothesis such as PEAD (post-earnings-announcement drift: Ball and Brown, 1968; Bernard and Thomas, 1990), accrual anomaly (Sloan, 1996; Xie, 2001), etc. Some of the possible explanations for this could be limited investor attention due to costly processing and information complexity (Bloomfield, 2002; Hirshleifer, Lim, and Teoh, 2002; Hirshleifer and Teoh, 2003) or underreaction due to slow diffusion of information (Hong and Stein, 1999).[16] The qualitative nature and high volume of the firm-initiated tweets and followers' engagement may make it difficult for the investors to process and incorporate this new information into prices concurrently. Therefore, the investors might take more time to right price the information in the changes in followers' engagement.

On the other hand, it is also possible that the market exhibits exuberance and overreacts to the buzz or excitement created by the changes in followers' engagement leading to overpricing (DeBondt and Thaler, 1985; Hong and Stein, 1999). In this scenario, one would expect the market to correct itself to the appropriate level in the subsequent periods (Chan, 2003). Hence, the observed overpricing will be followed by reversals. A third possibility is that the market correctly prices the information in the followers' engagement during the same period and there is no under or over-reaction subsequently. Therefore, even if the buzz created by the followers' engagement is informative, ex-ante it is not clear whether the aggregate information in the changes in followers' engagement gets incorporated in the stock prices during the concurrent period, or there's some underreaction or overreaction i.e., do changes in followers' engagement predict future stock returns. This leads to the following hypotheses stated in the *NULL FORM*:

Hypothesis 2A: Ceteris Paribus, a change in the followers' engagement volume is not associated with the firm's stock return during subsequent periods.

Hypothesis 2B: Ceteris Paribus, a change in each component (likes, retweets, replies) of the followers' engagement volume is not associated with the firm's stock return during subsequent periods.

3. Sample, Data Collection, Variables, and Research Design

3.1 Sample and Data Collection

[16] In addition, Hales (2007) shows that investor preferences can also significantly influence the manner in which information is processed and affect their expectations of future earnings performance. This could lead them to make investment decisions which may not be in their best interest.

I use a comprehensive sample of tweets, retweets, likes, and replies from the official Twitter accounts of firms for my study.[17] I cover all publicly-traded US firms listed on NYSE or AMEX or NASDAQ exchanges between 2006 and 2017. The paper focuses on the primary Twitter accounts of firms,[18] and the final data used in my study has approximately 17.9 million tweets by firms, and 183.8 million likes, 126.3 million retweets, and 32.9 million replies by their followers, from 2,197 unique Tweet firms. I use monthly data to test hypotheses 1 A & B. The sample period is from the first quarter of 2006 to the last quarter of 2017.[19]

I collect financial data of firms from Compustat, stock and market return data from CRSP, market factors data from Prof. Kenneth French's website, and analyst data from IBES. I also collect newspapers and press releases data from LexisNexis. My final data for the full sample comprises of 166,710 firm-quarters (46,090 Tweet firm-quarters) and 5,980 unique publicly-traded firms (2,197 unique Tweeting firms).[20]

3.2 Variables Description

In this section, I define the dependent variables and the variables of interest which I use to test the hypotheses outlined in Section 2.2.

Dependent Variables

[17] I employ the same sample of firm-initiated tweets which has been used for another working paper of mine "Determinants of Firms' Presence on and Use of Twitter: An Empirical Study" by Kang, Hosseini, Savickas and Singh (2019) for the analysis. The tweets and the corresponding engagement was collected using a combination of Twitter Application Program Interface (API) and web-scraping.

[18] Each Tweet firm has one Primary Twitter account. Some firms may also have additional Twitter accounts, which I refer to as Secondary Twitter accounts to cater to different regions, investor relations, customer services, recruitment etc. I do not include tweets from these Secondary accounts in my analysis.

[19] The company Twitter was created in March 2006.Starbucks was the first public firm in US to create a Primary Twitter account in November 2006. See https://twitter.com/starbucks for reference.

[20] I delete all observations with missing values of total assets, market value, net income, book-value of equity, revenue, and diluted EPS This sample is used for the analysis in Tables 6 and 7. I use all observations for the tests involving monthly stock returns as the dependent variable.

I use monthly excess stock returns (*EXCESS_RETURN*) as the dependent variable to test my hypotheses. I compute *EXCESS_RETURN* by subtracting the 1-month Treasury bill rate from the corresponding month's stock return for each firm.

Variables of Interest

The focus of my paper is to examine whether a firm's Twitter account's followers' change in engagement aggregated over a period provides incremental information that can help predict the firm's stock returns. The followers may respond by liking, retweeting, or replying to a firm's tweet. I define the collective response of the followers to a tweet as the *engagement* with that tweet. Each of these three components may be capturing a different dimension of the followers' engagement. A 'Like', by definition, represents a positive response or feedback by the follower even though it could be to a negative news tweet by the firm. In the case of a 'Retweet', a follower can also add her comments, which may be positive or negative. Finally, a 'Reply' involves considerably more time and effort of the follower as it commits her to write comments and share her opinion or feedback in the form of text. Reply, therefore, can represent either positive or negative feedback depending on the content.

The public and open-access nature of Twitter makes the followers' engagement a collaborative process, as anyone can view and build on it. Thus, engagement is representative of the followers' feedback for the firm's products, services, corporate disclosures, or any other information that the firm disseminates on its Twitter account. Whenever someone likes, retweets, or replies to a tweet, the tweet also becomes 'visible' to that person's followers. It is, therefore, important to note that engagement is only a *lower bound* on the extent to which a firm's dissemination has been 'seen' by the intended audience and the excitement or 'buzz' it has generated. One can also think about engagement as a measure of the efficacy of a firm's dissemination and communication efforts with its followers.

I separately aggregate the likes, retweets, and replies of all the tweets initiated by a firm over a period and take their logs as measures of each component of the followers' engagement - *LOG (LIKES)*, *LOG (RETWEETS) and LOG (REPLIES)*. I also add the likes, retweets, and replies for each tweet, aggregate them over a period and use the log of this sum as the combined measure of engagement of the firm's followers - *LOG (ENGAGEMENT)*. It is conceivable that the larger or consumer-facing firms may have more followers, tweet more, and, hence, also have higher engagement. To allay this concern, I also use a normalized measure of engagement by dividing *LOG (ENGAGEMENT)* by *LOG (TWEETS)*. This measure, *RESPONSE*, then represents the engagement per unit tweet for each period. I use the change specification as the variables of interest for testing my hypotheses – *CHANGE_LOG (LIKES)*, *CHANGE_LOG (RETWEETS), CHANGE_LOG (REPLIES), CHANGE_LOG (ENGAGE),* and *CHANGE_RESPONSE*. To mitigate the influence of outliers, I winsorize all continuous variables at 1% and 99% level.

3.3 Research Design

[Insert Figure 1 here]

Firms which have a presence on Twitter continuously disseminate information through tweets and followers of the Twitter account likewise respond in real-time, thus establishing an uninterrupted flow of publicly viewable communication between the two. The firm announces its earnings for the current quarter sometime during the next quarter; after the beginning but before the end of the next quarter. Therefore, the volume of a firm's followers' engagement (change in followers' engagement) during a period may be a leading indicator of the firm's performance in that quarter and maybe incrementally informative to capital market participants. This additional information is over and above the other known sources of concurrent information such as traditional media, firm's voluntary disclosures, and analysts' forecasts. The timeline for the flow of this information and its interaction with stock returns and earnings announcements is shown schematically in Figure 1.

Asset pricing models (Fama and French, 1993; Cahart, 1997; Fama and French, 2014) state that differences in common factor betas explain all the cross-sectional differences in stock returns and, hence, individual firm characteristics and idiosyncratic risk does not matter. Therefore, I examine the informativeness of the volume of followers' engagement during a given period using the Fama-French Five-Factor model (Fama and French, 2015). The model employs Fama-MacBeth (1973) monthly cross-sectional regressions with Newey-West (1987) corrected standard errors (two lags) used for calculating t-statistics.[21] The five Fama-French (FF) factors are – Market return (MKTRF), Size (SMB), Book-to-Market (HML), Operating Profitability (RMW), and Investment (CMA). Jegadeesh and Titman (1993) provide evidence that past winners tend to outperform past losers in the following years and, therefore, I include the Momentum factor too.

The equation used for testing Hypotheses 1A&B is (Model 1):

$$(R_{i,q,t} - Rf_{q,t}) = \Upsilon_0 + \Upsilon_1 CHANGE\_ENGAGEMENT\_VOLUME_{i,q,t} + \Upsilon_2 MOM_{q,t} + \Sigma\, \Upsilon_j FAMA\text{-}FRENCH\ FACTORS_{q,t} + \Sigma\, \Upsilon_k\, CONTROLS_{i,q,t} + \varepsilon_{i,q,t} \quad (1)$$

where *i* indexes the firm, *q* indexes the quarter, and *t* indexes the month, $R_{i,q,t}$ is the monthly buy and hold return, and $Rf_{q,t}$ is 1-month T-bill rate, $(R_{i,q,t} - Rf_{q,t})$ is the monthly excess stock return, measures of $CHANGE\_ENGAGEMENT\_VOLUME_{i,q,t}$ are as defined in the previous section and Appendix A. $MOM_{q,t}$, and $FAMA\text{-}FRENCH\ FACTORS_{q,t}$ are the factor loadings of momentum and FF five factors, respectively. There is a lot of information about a firm's likely performance, which is released by the firms' managers, analysts, and in traditional media during the month. This information may lead to investors updating their beliefs about the firm, which might affect the stock prices. Therefore, I include controls for any changes in consensus analyst forecast, the number of upward and downward revisions in analyst stock recommendations, earnings surprise during the last quarter, number of press releases by the firm, and number of articles about the firm appearing in newspapers. I predict that $\Upsilon_1 \neq 0$, which implies that the change in followers' engagement volume is informative to capital market participants beyond the FF and Momentum factors, and the other concurrent information about the firm coming to the market. I also test

[21] I use prior 36 months data to, first, compute the factor betas on a monthly rolling basis for each firm. This ensures that the factor beta used in any month has been computed using previous 36 months data. I require at least 12 observations for performing the rolling regressions. Next, I perform cross-sectional regressions for each month and, finally, take the time-series average of the slopes in monthly regressions, with Newey-West corrected standard errors used for calculating t-statistics to account for any autocorrelation (two lags).

Hypotheses 2A&B using the same model but with the lagged values of *CHANGE_ENGAGEMENT_VOLUME* as the variables of interest.

I apply the model to three different samples. The first sample, referred to as the full sample, has all firm-months - Tweet as well as all non-Tweet firm-months – and allows me to observe the informational effect of engagement volume relative to the control group (non-Tweet) firms. The second sample, called the *Tweet sample,* has only Tweet firm-months and allows me to interpret the coefficient of engagement volume as having an association with firm performance. This is because the engagement level of the firm's followers is a measure of the buzz or enthusiasm about the firm and, hence, may affect the firm's sales and earnings. The last sample excludes firms that never created a Twitter account from the full sample, allowing me to observe the informational effect of engagement for the tweeting firm relative to the period when that firm did not have a Twitter account. I report most of the results using the full sample and use the second and third samples for robustness checks. I have tried to control for other known public sources of information such as press releases, newspapers, earnings announcement, and analysts. However, I cannot rule out the possibility of an omitted correlated variable that might be influencing both the followers' engagement volume and the firm performance.

4. Descriptive Statistics

[Insert Figure 2 here]

There has been a rapid increase in both the number as well as the proportion of firms that use Twitter to disseminate information and engage with their stakeholders. As shown in Figure 2, the percentage of firms that use Twitter has increased from 0% in 2006 to more than 50% in Dec 2017, indicating that Twitter is a popular social media platform used by firms.[22]

[Insert Tables 1 A, B, C, and D here]

[22] HKSS (2019) document that 52% of publicly-traded US firms had a Twitter account as of Dec 31, 2017.The proportion of firms using Twitter for dissemination is slightly lesser than this. One of the reasons could be that 73 new firms joined Twitter in 2017 and there might be a gap between when a firm joins Twitter and the time it starts tweeting.

Panel A of Table 1 shows the descriptive statistics of the key variable for the full sample of 166,710 firm-quarters - both Tweet as well as all non-Tweet firm-quarters (also includes firms which do not have a Primary Twitter account as on Dec 31, 2017). Panel B of Table 1 shows the descriptive statistics for the tweet and engagement variables for the Tweet subsample of 46,090 Tweet firm-quarters (includes only firms that have a Twitter account and started tweeting during the sample period. '*Tweet'* firms tweet 388 times, on average, every quarter and generate an average of 3,988 likes, 2,740 retweets, and 716 replies – engagement of 7,444 – from the followers. There is wide variation in the use of Twitter – firms at 25% (75%) percentile have 16 (232) tweets and 68 (1,387) engagement per quarter. On average, there is an increase in tweets (engagement) of 16 (718) per firm-quarter. Again, there is a wide variation in the distribution of these variables as firms at the 25th percentile experience a decrease in tweets (-17), and engagement (-63) whereas firms at the 75th percentile experience a net increase in tweets (24) and engagement (148) every quarter.

In comparison, as shown in Panel C, these 'Tweet' firms have, on average, 14 press releases, appear 58 times in newspapers, and twelve analysts following them every quarter. Thus, these firms might be using Twitter to disseminate information not only about financial disclosures and other corporate announcements but for other purposes as well. This suggests that the followers' engagement with the firms' tweets may represent new information to the market participants. Panel D shows the time-trend of Tweet firm-quarters, total tweets, total likes, total retweets, total replies, and total engagement over the sample period of 2006 to 2017.[23] It is clear from the table that there has been an explosive growth in the usage of Twitter by firms as well as followers' engagement, especially after 2008. However, there has been a dip in the number of tweets in 2017 though not in engagement.[24]

[Insert Figures 3A and B here]

[23] There is only one firm which joined Twitter in 2006 but did not tweet during that year. Hence, there are zero tweets and engagement in 2006.

[24] One of the reasons could be that Twitter increased the number of characters which can be used in a tweet from 140 to 280 in November 2017.

Figures 3 A & B show the trend of average firm-initiated tweets and follower's average engagement for Fama-French ten industries. The trend is broadly similar for all the industries with telephone & television transmission and shops (retail, wholesale) industries having the highest frequency of tweets as well as engagement per firm-quarter.

[Insert Tables 2 A and B here]

Panel A of Table 2 shows the Pearson's correlation between tweet and engagement variables for the Tweet firm-quarters sample. There is a very high correlation between tweet and engagement variables. There is also a very high correlation between the different components of engagement – likes, retweets, and replies – which suggests that they may be manifestations of the same latent construct. Panel B shows the Pearson's correlation between engagement variables and variables of interest. On a univariate basis, stock returns and the variables of interest – *CHANGE_LOG(LIKES)*, *CHANGE_LOG(RETWEETS)*, *CHANGE_LOG(REPLIES)*, and *CHANGE_LOG(ENGAGE*) – are strongly positively correlated, which provides initial support to my conjecture that change in the followers' engagement may be informative to capital market participants. In the next section, I perform a multivariate analysis to test the hypotheses further.

5. Empirical Results

In this section, I discuss the results of testing my hypotheses using the model presented in Section 3.3.

5.1 Stock Returns and Followers' Engagement

I use Model 1 to test Hypotheses 1A&B and 2A&B in this section. I employ Fama-MacBeth cross-sectional regressions to the Fama-French five-factor model to examine the association between the changes in followers' engagement and monthly stock returns. The dependent variable is the monthly excess stock returns computed as the excess stock returns over the 1-month Treasury bill rate. The slopes reported in the tables are the coefficients of change in engagement volume variables, the common factor betas, and control variables. T-statistics have been calculated using Newey-West corrected standard errors to account for any autocorrelation (two lags) in the error terms.

Stock Returns and Contemporaneous Followers' Engagement

[Insert Table 3 here]

I first test for the association between a firm's followers' engagement volume and firm's monthly stock return during the same month, which is Hypotheses 1A&B, using a base model similar to Model 2 of Bartov et al. (2018).[25] I use the analyst following, an indicator variable for loss, an indicator variable for the fourth fiscal quarter, and institutional holding as control variables. I use the full sample which includes both Tweet and non-Tweet firm-months. Table 3 displays the results of the base model. All the variables of interest, except *CHANGE_RESPONSE* – are positive and significant at the 1% significance level. This implies that there is a strong positive association between the monthly stock returns and changes in the followers' engagement. The coefficient of *LOSS* is negative and significant as expected. The negative and significant coefficient of the number of newspaper articles could be because investors may be more active in following and utilizing the information in the followers' engagement when the media coverage is lower.

[Insert Tables 4A&B here]

There is a lot of information about a firm's likely performance that is released concurrently by firms' managers and analysts during the month. This information may lead to investors updating their beliefs about the firm, which might affect the stock prices. Therefore, I augment the base model used for the analysis in Table 3 and include changes in monthly analyst consensus forecast, the number of upward

[25] Bartov et al. (2018) use daily stock returns for their analysis as their study is centered around the earnings announcement. Their dependent variable is the Carhart's (1997) buy-and-hold abnormal stock returns for the firm over the event window period. My study uses monthly stock returns as I am interested in examining the effect of the followers' engagement on the firm's monthly stock returns. Therefore, I use the excess stock returns over the one-month Treasury Bill for the firm as my dependent variable and, then, control for the Fama-French five factors and the Momentum factor.

and downward revisions in analyst recommendations, last quarter's earnings surprise,[26] and the number of press releases by the firm, as additional controls. I refer to this as my main model and use it for all subsequent analyses whenever monthly stock returns is the dependent variable.

Next, I examine whether a change in the followers' engagement volume and its components is informative to the capital market participants using the main model. Panel A of Table 4 displays the results for the full sample which has all Tweet and non-Tweet firm-months. The coefficients of all the variables of interest – *CHANGE_LOG (LIKES), CHANGE_LOG (RETWEETS), CHANGE_LOG (REPLIES), CHANGE_LOG (ENGAGE),* and *CHANGE_RESPONSE* are positive and statistically significant at the 1% level. Most of the other sources of concurrent information, such as the number of upward and downward revisions of analyst stock recommendations and earnings surprise are also significant in the expected direction.

The results for the Tweet sample – only Tweet firm-months – are shown in Panel B and are qualitatively similar to those for the full sample, though they are much weaker. However, all the factor betas are not priced in both Tables 3 and 4. This could be due to the high correlation between the variables of interest and some of the factor betas (SMB, HML, MOM, and RMW) and the much shorter time period (2006 to 2017) used for the analysis.[27]

I interpret these results to mean that change in followers' engagement volume represents a *new information* source for the capital market participants over and above the common factor betas and other sources of concurrent information about the firm. The results also suggest that this new information is getting priced by investors during the same period. As explained in Section 3.2, likes, retweets, and replies may represent different dimensions of engagement, and each one of them may or may not be informative. I find that the components of engagement are also individually informative. Another interpretation of the results is that a change in a firm's engagement volume is a coincidental indicator of the stock returns as it

[26] I use last quarter's earnings surprise because prior literature has shown that the market underreacts to earnings surprise and leads to PEAD (Ball and Brown, 1968; Bernard and Thomas, 1990).
[27] Petkova (2006) also shows that some of the factor loadings lose their explanatory power because of the correlation with innovation which is his variable of interest in the study.

can be observed in real-time by managers and capital market participants. This implies that the ‘buzz’ created by the followers is meaningful and not merely random noise.

Stock Returns and Lagged Followers’ Engagement

[Insert Table 5 here]

The results of Tables 3 & 4 show that the followers’ engagement gets impounded into stock prices during the same period. However, I still can’t say whether the market has underreacted or overreacted. I try to answer this question in this section by testing Hypotheses 2A&B. I examine whether a change in engagement volume continues to be informative to the market during the subsequent months too. Panel A of Table 5 displays the results for one month lagged changes in the followers’ engagement. The coefficients of all the variables of interest, except *CHANGE_RESPONSE*, are positive and significant at 1% level. This suggests that the market had underreacted earlier and is still impounding the *new information* contained in changes in engagement volume into the stock prices. However, the magnitude and significance of the coefficients of one-month lagged variables of interest are lower compared to that of the corresponding concurrent variables in Panel A of Table 4 e.g., the coefficient of $CHANGE\_LOG\_LIKES_{i,q,t-1}$ is 0.002 (p-value of 2.959) compared to 0.003 (p-value of 3.619) for the coefficient of the corresponding concurrent variable in Column 1 of Panel A (Table 4). This also implies that there has been no overreaction.

Panel B presents the results for two months lagged variables of interest. The coefficients of the second month lagged variables of interest, though positive, are all insignificant. Results in Panels A&B imply that the market underreacts somewhat to the changes in followers’ engagement as it takes one additional month for fully pricing this *new information*. Another way of stating these findings is that the changes in followers’ engagement continue to be value relevant for the next month but not for the month after that. Since there has been no reversal of stock returns in either of these two subsequent months, it can be concluded that the positive association between monthly stock returns and the variables of interest in Tables 3&4 was not due to overreaction. Thus, changes in the followers’ engagement are also forward-looking and predict the next month’s stock returns. This observed underreaction could be because the market participants take some time to fully process the information due to the large volume and the qualitative nature of followers' engagement.

Taken together, Tables 3 to 5 provide strongly suggest that changes in engagement volume are value relevant. Results of Tables 3 and 4 imply that the aggregate information in followers' engagement in a given period represents new value relevant information to the market participants during the same period. Results of Table 5 indicate that the market also underreacts to this information, maybe because of its large volume and qualitative nature, and it takes an additional month to impound it into stock prices fully. Therefore, the change in volume of a firm's followers' engagement is *incrementally* informative to the market participants beyond the other known sources of concurrent information such as press releases, newspaper coverage, and voluntary disclosures. Followers' engagement is, thus, indicative of the firm's performance.

5.2 Additional Tests

In this section, I perform some further tests to test the association between the engagement volume and firm value. I also try to address what is the new information in the followers' engagement, which the investors find valuable.

Firm-Value and Engagement Volume

The results in Section 5.2 suggest that the changes in followers' engagement are associated with stock returns. I further verify the results of the previous section by using *TOBINS'Q* as the measure of firm-value and the level of engagement volume variables as the independent variables. I use the following OLS regression equation for the analysis:

$$TOBINS'Q_{i,q} = \beta_0 + \beta_1 ENGAGEMENT\_VOLUME_{i,q} + \Sigma\beta_j CONTROLS_{i,q} + YEAR\_QTR\ FIXED\text{-}EFFECTS + FIRM\ FIXED\text{-}EFFECTS + \varepsilon_{i,q} \quad (2)$$

where *i* indexes the firm and *q* indexes the quarter.

[Insert Table 6 here]

Table 6 shows the results of testing the association between the different measures of engagement volume and *TOBIN'SQ* using OLS regression for the full sample. I use year-quarter and firm fixed-effects to control for any time trends and time-invariant firm characteristics, respectively. I also cluster the standard errors by firm. The coefficients of *LOG (LIKES)*, *LOG (RETWEETS)*, and *LOG (ENGAGEMENT)* are positive and statistically significant at the 10% level. The results are economically significant too. I provide an interpretation of the results in column 4 for reference. One standard deviation increase in *LOG (ENGAGEMENT)* is associated with an approximately 2% increase in the value of *TOBIN'SQ* (2.515* 0.008 = 2.01 %). However, *LOG (REPLIES)* is not significant. One of the reasons for this could be that I use only the count of replies as my explanatory variable, whereas the text of the replies may also be playing a role. In untabulated results, I find even stronger results using the sample of only Tweet firms. These results suggest that the followers' engagement has a positive association with firm-value.

What is the Information in Followers' Engagement?

The results in Section 5.1 suggest that the aggregate information in the volume of followers' engagement with firm-initiated tweets gets priced by the capital market over two months. A key question to then ask is, "What is this *new information* in the followers' engagement which the market participants find valuable?" In this section, I probe this question. Marketing studies have shown that firms use their presence on social media for brand building, marketing campaigns, and sales promotions, in addition to their traditional marketing activities (Trusov, Bucklin and Pauwels, 2009; Erdogamus and Cicek, 2012). Initially, firms focused on acquiring more followers. However, they soon realized that the response or buzz they can generate from the followers is a more important measure of the effectiveness of their social media marketing activities. Consequently, firms started adopting new and innovative strategies and techniques to leverage social media for stimulating customer engagement and demand (Schniederjans, Cao and Schniedarjans, 2013; Rishika, Kumar, Janakiraman and Bezawada, 2013; Gong, Zhang, Zhao and Jiang, 2017; Lee, Hosanagar and Nair, 2018).

Therefore, the volume of a firm's followers' engagement aggregated over a given period may convey incremental information about the firm's sales and sales growth during that period; a high level of engagement represents more excitement or buzz by the followers and, therefore, is likely to be associated with higher sales. Similarly, a change in the level of engagement over a period may be a leading indicator of the sales growth to be expected during that period. However, prior literature also shows that it is inconclusive whether and how tweeting influences product demand and sales (Gong et al., 2017). Additionally, all firms may not have the same ability to harness the power of social media for increasing demand for their products and services, or the followers may not be representative of the customer base of the firm. Therefore, ex-ante it is not clear whether the aggregate level of followers' engagement is informative about the likely sales of the firm during the period. I use the following OLS regression equation for the analysis:

$$SALES\_GROWTH_{i,q} = \beta_0 + \beta_1 CHANGE\_ENGAGEMENT\_VOLUME_{i,q} + \Sigma\beta_j CONTROLS_{i,q} + YEAR\_QTR\ FIXED\text{-}EFFECTS + FIRM\ FIXED\text{-}EFFECTS + \varepsilon_{i,q} \quad (3)$$

where i indexes the firm and q indexes the quarter.

[Insert Table 7 here]

Firms with a Twitter account may be using that platform to communicate and engage with their followers about their products and services, sales promotions, new product offerings and also to respond to any customer service issues or queries which customers might raise (Lee et al., 2018; Gong et al., 2018). I next test the relationship between changes in followers' engagement volume and sales growth using OLS regression for the full sample in Table 7. I use year-quarter and firm fixed-effects to control for any time trends and time-invariant firm characteristics, respectively. I also cluster the standard errors by firm. I include advertising expense scaled by assets, change in deferred revenue scaled by last quarter's sales, the log of previous quarter's sales and previous quarter's sales growth as additional controls (Tang, 2018) because these variables might also affect current quarter's sales and, hence, the sales growth. The coefficients of all the Variables of Interest are positive and significant at 1% level (except the coefficient of *RESPONSE* which is negative though insignificant). This indicates that there is a strong positive association between change in the volume of followers' engagement and sales growth of the firm. In untabulated results, I also find that change in the followers' engagement volume does not predict the next quarter's sales growth. I interpret this to mean that the followers' engagement pertains mainly to the underlying business operations of the firm for the same period.

Tables 7 provides strong evidence that the engagement volume of a firm's Twitter account is informative about the likely sales growth of the firm during the period. Hence, a firm's followers' engagement volume may be a leading indicator of its likely business performance during that period to the investors. This is because the firm announces the current quarter's earnings during the next quarter. It is this predictive ability of the change in followers' engagement volume about the firm's sales growth during that period that the capital market participants may be finding valuable and incorporating into stock prices.

Engagement Volume - Information or Attention?

[Insert Table 8 A and B here]

An alternative explanation for the findings in Section 5.1 could be that the followers' engagement is not new information, but the buzz it creates may be attracting investor attention. Investors may then be buying the stock because of this increased attention and not because of the informative value of the followers' engagement. Earnings announcement by a firm is the most anticipated event and generates the maximum attention from investors (Curtis et al., 2016). Therefore, I repeat the test of Table 4A after removing the months of earnings announcement to rule out this alternative explanation. If my results are driven by investor attention, then I should not find a positive association between the change in followers' engagement volume and stock returns. The results, shown in Panel A of Table A, indicate that changes in followers' engagement are still value relevant and, therefore, must signify new information to the capital market participants.

The results of Table 7 suggest that the followers' engagement is associated with the business operations of the firm during the same period. The findings in Section 5.1 imply that the changes in followers' engagement are informative only during the same and the next month but not subsequently. We also know that the earnings for the previous quarter are announced sometime during the month t of the current quarter. This suggests that the change in followers' engagement in month t should not have any association with the returns around the earnings announcement. Similarly, the changes in followers' engagement during months t-1 and t-2 should not be associated with the returns around the earnings announcement. I test this using the three-day cumulative abnormal return around the earnings announcement. I deduct the daily market return from the daily stock return and sum this abnormal return over three days around the earnings announcement [-1;+1] to compute the 3-day cumulative abnormal return (CAR) for each firm. I then regress CAR on the change in engagement during the same month as well as the lagged values of the previous two months. The results displayed in Panel B of Table 8 show that there is no association between the changes in engagement volume during the same or last two months and CAR around the earnings announcement. As documented by prior literature, earnings surprise gets impounded in the stock prices. This also provides further evidence that the positive association between the followers' engagement and stock returns is not due to investor attention.

5.4 Robustness Tests

In this section, I perform a series of robustness tests to check whether the results are sensitive to using different samples, specifications, and alternative measures.

[Insert Table 9 A and B here]

Thus far, I have only used firm-initiated tweets from the Primary Twitter account of the firm. However, some firms may, in addition to the Primary Twitter account, have other Twitter accounts that cater to specific geographies, business segments or functions. Therefore, I repeat the analysis using engagement from all the Twitter – Primary and Secondary – accounts of the firms.[28] The results of testing Hypothesis 1 A & B using this expanded tweet sample, shown in Panel A of Table 9, suggest qualitatively similar results as in Panel A of Table 4. There might be differences in tweet and engagement volume across industries driven by the type of products sold, type of consumers as well as how other peer firms in the industry utilize Twitter. Therefore, I compute another measure of engagement volume after adjusting for the median SIC 2-digit engagement volume. The results, displayed in Panel B of Table 9, remain qualitatively similar using these median industry-adjusted engagement volume measures.

There is a very high correlation between the (change in) volume of tweets and the (change in) volume of followers' engagement. Therefore, an alternative explanation could be that the documented results are driven by the volume of firm-initiated tweets rather than the volume of the followers' engagement. This would suggest that when firms tweet more, they are disseminating more information which the investors find valuable. To rule out this alternative hypothesis, I use an alternative measure of the followers' engagement. I regress the change in followers' engagement on change in the firm's tweet volume. I then rerun the test in Panel A of Table 4 including the residuals from this regression and change in tweet volume as explanatory variables - both these variables are orthogonal to each other. In untabulated results, I find that the coefficient of the residuals is positive and significant. This suggests that the followers' engagement represents new value-relevant information.

I also apply Model 1 to a subsample of the full sample, which excludes firms that have never created a Twitter account. Doing this allows me to observe the informational effect of changes in engagement on the Tweet firm relative to when the firm did not have a Twitter account. The statistical results remain unchanged. I also use industry fixed-effects (Fama-French 48 or SIC 2-digit) instead of firm fixed-effects and find even stronger results. These tests show that the findings are not sensitive to the use of different samples, model specifications, and alternative measures of variables of interest.

[28] In my sample 195 firms have 1,209 Secondary accounts in addition to having a Primary account. All Twitter accounts – Primary and Secondary – have approximately 29 million tweets, 238 million likes, 170 million retweets and 38 million replies.

6. Conclusion

Twitter has, arguably, emerged as the most popular social media for the dissemination of information by firms. Extant literature has studied the motivation and consequences of firms tweeting. However, firms tweet not only to disseminate information but also to connect with their stakeholders and elicit their response and feedback. In this paper, I focus on the engagement of the followers with the firm's tweets as this is a relatively new phenomenon that has not been explored before. I study the aggregate information in the followers' engagement on firms' Primary Twitter accounts. Specifically, I examine whether the volume of the followers' engagement is informative to capital market participants. I find results that suggest that changes in followers' engagement volume convey incremental informative to the investors over and above the information contained in other known sources of information such as press releases, newspaper coverage, changes in consensus analyst forecast, and voluntary disclosures. The finding that the followers' engagement with a firm's tweets is informative at the aggregate level is of particular interest to investors and the firm's managers.

The results also suggest that the change in followers' engagement volume helps predict the firm's future stock returns. In particular, evidence suggests the capital market underreacts to the engagement information and that it takes two months for the capital market to fully impound the information into stock prices. This is an important finding which should be useful to managers and investors. I also find that the capital market underreacts to the information that changes in the followers' engagement volume represents. The results also suggest that changes in the followers' engagement are incrementally informative about the firm's sales growth during the same period. This may be the source of information which the capital markets find valuable. Thus, taken together, this suggests that the followers' engagement is informative about the firm's performance.

However, I don't make any claims of causality as there may be an unobservable omitted correlated variable influencing both the followers' engagement volume and the firm's financial performance. Also, Twitter is a subset of the overall social media engagement effort by a firm - most firms have a presence on other social media platforms such as Facebook, YouTube, and Instagram, etc.

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Appendix A

Variables Description

Dependent Variables	
CAR	Excess of daily stock return over the daily market return summed over three days around the earnings announcement (-1,0,1)
EXCESS_RETURN	Excess of the firm's monthly stock return over the 1-month Treasury-bill rate ($R_{i,q,t} - Rf_{q,t}$)
SALES_GROWTH	(Sales for the current quarter / Sales for the previous quarter) -1
TOBINS' Q	Market value of assets/book value of assets=(Book value of assets + Market value of Common Stock - Book value of Common Stock)/Book Value of Assets
Variables of Interest	
CHANGE_LOG(ENGAGE)	Log(Engagement) of the current period minus Log(Engagement) of the previous period (month or quarter)
CHANGE_LOG(LIKES)	Log(Likes) of the current period minus Log(Likes) of the previous period (month or quarter)
CHANGE_LOG(REPLIES)	Log(Replies) of the current period minus Log(Replies) of the previous period (month or quarter)
CHANGE_LOG(RESPONSE)	Response of the current period minus Response of the previous period (month or quarter)
CHANGE_LOG(RETWEETS)	Log(Retweets) of the current period minus Log(Retweets) of the previous period (month or quarter)
LOG(ENGAGEMENT)	Natural log of the sum of total retweets, total likes and total replies by followers of a firm's Twitter account during the current period (month or quarter)
LOG(LIKES)	Natural log of total likes by the followers of a firm's Twitter account during the current period (month or quarter)
LOG(REPLIES)	Natural log of total replies by the followers of a firm's Twitter account during the current period (month or quarter)
LOG(RETWEETS)	Natural log of total retweets by the followers of a firm's Twitter account during the current period (month or quarter)
RESPONSE	Log(Engagement) divided by Log(Tweets) for each Tweet firm-period (month or quarter)
Control Variables	
ACQUISITION	Indicator variable equal to 1 if the firm made any acquisitions during the current quarter
ADV_EXP_QTR	Annual advertising expense divided equally over the four quarters and scaled by average total assets of the quarter

CMA	Slope of Conservative Minus Aggressive Factor (CMA from Fama-French Factors)
CHANGE_ANALYST_CONSENSUS	Change in the monthly analyst consensus forecast
CHG_BACKLOG	Change in quarterly deferred revenue scaled by last quarter’s sales
HML	Slope of High minus low Factor (HML from Fama-French Factors)
INSTI	The proportion of the firm’s shares held by Institutional investors
LEVERAGE	Sum of long-term debt and debt in current liabilities scaled by total assets of the firm at the end of the current quarter
LOG(ASSETS)	Natural log of the firm’s total assets at the end of the current quarter
LOG(PRESSRELEASES)	Log of one plus the number of press releases issued by the firm and distributed via a news provider during the quarter.
LOG(NEWSPAPERS)	Log of one plus the number of news articles written about a firm during the quarter.
LOG(NUM_ANALYSTS)	Natural Log of one plus number of analysts following (from IBES database) during the quarter
LOSS	1 if income before extraordinary items is negative during the quarter, and 0 otherwise
MKTRF	Slope of Excess return on the market (CAPM) Factor (MKTRF from Fama-French Factors)
MOM	Slope of Up minus down Factor (MOM from Fama-French Factors – Monthly Frequency)
MTB	The ratio of the market value of equity to book value of equity at the end of the current quarter
NUM_RECO_DOWN	Number of downward revisions in stock recommendations by analysts during the current month
NUM_RECO_UP	Number of upward revisions in stock recommendations by analysts during the current month
Q4	1 if it’s the fourth fiscal quarter, and 0 otherwise
RMW	Slope of Robust Minus Weak Factor (RMW from Fama-French Factors)
ROA	Net Income in the current quarter scaled by average assets of the firm at the end of the current and previous quarters
SMB	Slope of Small minus Big Factor (SMB from Fama-French Factors)
UE_EARNINGS	Actual EPS for the quarter (reported in I/B/E/S) minus the most recent consensus analyst EPS forecast for the current quarter announced after the end of the quarter, scaled by previous quarter-end’s stock price

Figure 1: Aggregation of Information: Firm's Twitter Account's Followers' Engagement

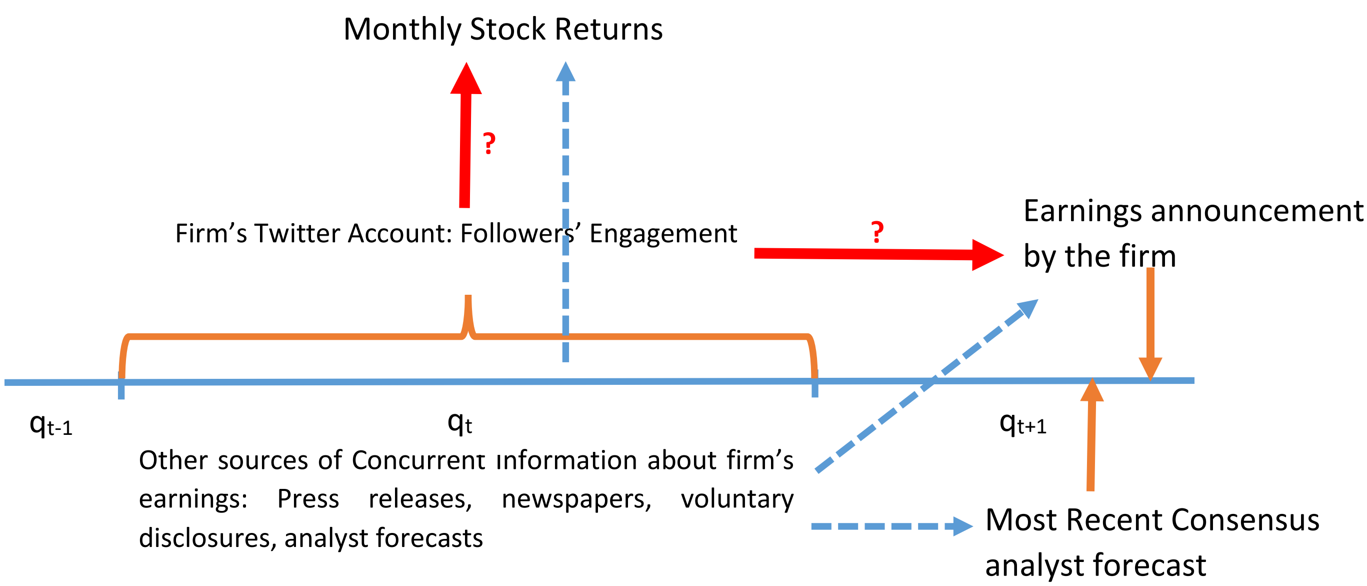


Figure 2: Time-Trend of Proportion of Firms which Tweet

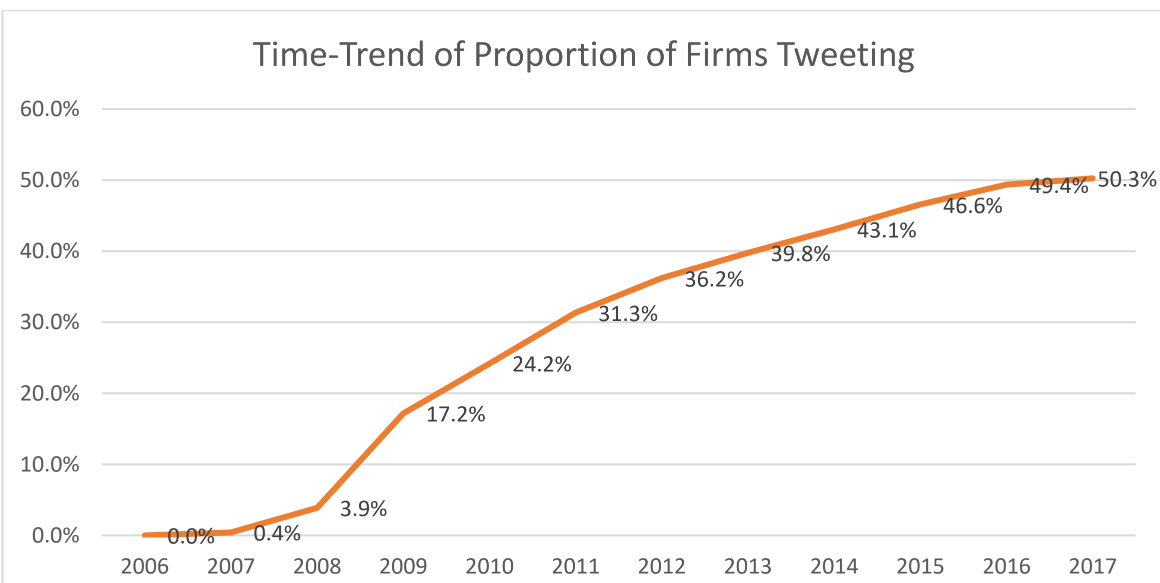


Figure 3: Time Trend of Tweets and Engagement: Fama-French Ten Industry Classification

Figure 3A: Time-Trend of Average Tweets

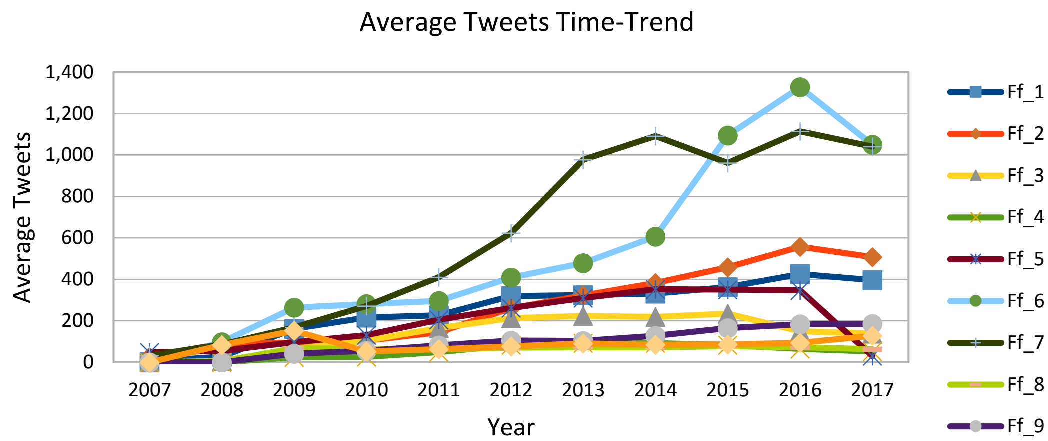
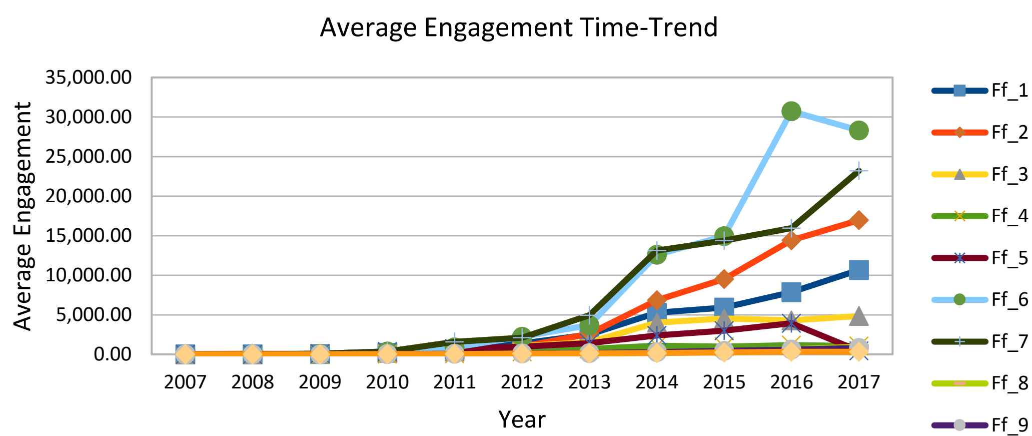


Figure 3B: Time-Trend of Average Engagement



Fama-French Ten Industry Classification

Ff_1	Consumer Non-Durables
Ff_2	Consumer Durables
Ff_3	Manufacturing
Ff_4	Energy
Ff_5	Computers, Software, and Electronic Equipment
Ff_6	Telephone and Television Transmission
Ff_7	Shops (Wholesale, Retail, and Some Services)
Ff_8	Health
Ff_9	Utilities
Ff_10	Other

Table 1: Descriptive Statistics of Key Variables

Panel A: Key Variables for All Firm-quarters

Variables	# Firm-quarters	Mean	Median	Std. Dev.	P25	P75
ASSETS	164,275	5283.701	621.513	18504.44	137.137	2727
MTB	164,275	3.121	2.036	5.837	1.177	3.672
LEVERAGE	164,275	0.599	0.207	2.063	0.000	0.739
NUMBER_ANALYSTS	164,275	10.289	8.000	7.811	5.000	14.000
SALES_GROWTH	158,329	0.052	0.019	0.322	-0.056	0.101
MARKET VALUE	164,275	4011.458	629.818	10793.460	151.252	2517.776
TOBINS'Q	164,270	2.160	1.529	1.913	1.128	2.367
PRESS_RELEASES	164,275	5.807	0.000	23.737	0.000	3.000
NEWSPAPERS	164,275	31.338	1.000	210.275	0.000	8.000
STOCK_RET_QTR	116,451	0.028	0.015	0.248	-0.112	0.144
INST	113,911	0.583	0.645	0.301	0.345	0.820
LOSS	164,275	0.333	0.000	0.472	0.000	1.000
Q4	164,275	0.241	0.000	0.428	0.000	0.000

Panel B: Tweet and Engagement Variables for Tweet Firm-quarters

Variables	# Tweet Firm-quarters	Mean	Median	Std. Dev.	P25	P75
TWEETS	46,090	387.995	71.000	2621.358	16.000	232.000
LIKES	46,090	3987.829	122.000	75834.320	24.000	504.000
RETWEETS	46,090	2739.959	128.000	49992.380	25.000	532.000
REPLIES	46,090	715.811	81.000	5429.700	17.000	286.000
ENGAGEMENT	46,090	7443.599	344.000	124637.800	68.000	1387.000
CHANGE_TWEETS	46,090	15.816	0.000	963.848	-17.000	24.000
CHANGE_LIKES	46,090	496.191	3.000	24870.660	-20.000	59.000
CHANGE_RETWEETS	46,090	185.076	1.000	19798.700	-26.000	53.000
CHANGE_REPLIES	46,090	37.152	0.000	2166.263	-18.000	29.000
CHANGE_ENGAGEMENT	46,090	718.419	6.000	42624.650	-63.000	148.000
LOG(LIKES)	46,090	4.705	4.812	2.396	3.219	6.225
LOG(RETWEETS)	46,090	4.724	4.860	2.361	3.258	6.279
LOG(REPLIES)	46,090	4.229	4.407	2.103	2.890	5.659
LOG(ENGAGEMENT)	46,090	5.620	5.844	2.515	4.234	7.236
RESPONSE	46,090	1.347	1.355	0.464	1.264	1.507
CHANGE_LOG(LIKES)	46,090	0.092	0.003	0.866	-0.237	0.396
CHANGE_LOG(REPLIES)	46,090	0.071	0.000	0.867	-0.262	0.368
CHANGE_LOG(RETWEETS)	46,090	0.053	0.000	0.816	-0.265	0.327
CHANGE_LOG(ENGAGE)	46,090	0.228	0.032	1.268	-0.245	0.462
CHANGE_RESPONSE	46,090	0.005	0.000	0.188	-0.025	0.036

Panel C: Key Variables for Tweet Firm-quarters

Variables	# Tweet Firm-quarters	Mean	Median	Std. Dev.	P25	P75
ASSETS	46,090	9467.643	1089.859	27280.050	231.171	5092.600
MTB	46,069	3.675	2.451	6.059	1.424	4.362
LEVERAGE	45,487	0.631	0.253	1.997	0.000	0.790
NUMBER_ANALYSTS	34,983	12.443	10.000	8.984	5.000	18.000
SALES_GROWTH	45,013	0.044	0.020	0.266	-0.043	0.090
MARKET VALUE	46,090	7210.254	1311.921	15453.410	281.632	5480.767
TOBINS'Q	46,090	2.292	1.679	1.834	1.235	2.601
PRESS_RELEASES	46,090	13.730	2.000	38.644	0.000	12.000
NEWSPAPERS	46,090	57.697	3.000	298.088	0.000	17.000
STOCK_RET_QTR	34,946	0.039	0.028	0.220	-0.085	0.143
INST	32,096	0.598	0.667	0.279	0.428	0.801
LOSS	46,090	0.311	0.000	0.463	0.000	1.000
Q4	46,090	0.251	0.000	0.434	0.000	1.000

Panel D: Time-Trend of Tweets and Engagement

Year	# Tweet Firm-quarters	Tweets	Likes	Retweets	Replies	Engagement
2006	0	0	0	0	0	0
2007	40	1,124	1,526	1,483	1,164	4,173
2008	309	21,858	26,580	26,002	22,096	74,678
2009	1,797	213,141	289,637	252,754	213,619	756,010
2010	3,121	444,888	580,530	1,053,240	445,454	2,079,224
2011	4,031	783,690	1,104,725	2,724,679	1,133,547	4,962,951
2012	4,827	1,393,344	2,349,068	4,876,436	2,415,582	9,641,086
2013	5,432	2,077,894	5,964,379	10,482,755	3,845,277	20,292,415
2014	6,076	2,725,456	20,178,432	22,539,463	5,525,100	48,242,990
2015	6,796	3,133,937	32,066,559	26,136,655	5,871,381	64,074,598
2016	7,260	3,894,984	55,033,806	31,265,103	6,901,832	93,200,758
2017	6,401	3,192,392	66,203,815	26,926,152	6,616,672	99,746,591
Total	46,090	17,882,708	183,799,057	126,284,722	32,991,724	343,075,474

Panel A shows the descriptive statistics of key variables for the full sample comprising of both Tweet as well as all Non-tweet firm-quarters

Panels B & C show the descriptive statistics of tweet and engagement variables and key variables for the sub-sample comprising of Tweet firm-quarters only (firms which have a Twitter account and have started tweeting)

Panel D shows the time- trend of Tweet Firm-quarters, Tweets, Likes, Retweets, and Replies from 2006 to 2017.

All variables are as defined in Appendix A

Table 2: Pearson Correlation for Tweet Firm-quarters

Panel A: Pearson Correlation between Tweet and Engagement Variables for Tweet Firm-quarters

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
LOG(TWEETS)	1										
LOG(LIKES)	0.942***	1									
LOG(RETWEETS)	0.958***	0.983***	1								
LOG(REPLIES)	0.987***	0.964***	0.977***	1							
LOG(ENGAGEMENT)	0.962***	0.990***	0.993***	0.979***	1						
CHANGE_LOG(TWEETS)	0.133***	0.0801***	0.088***	0.115***	0.103***	1					
CHANGE_LOG(LIKES)	0.213***	0.199***	0.201***	0.207***	0.214***	0.738***	1				
CHANGE_LOG(RETWEETS)	0.199***	0.170***	0.190***	0.190***	0.195***	0.735***	0.957***	1			
CHANGE_LOG(REPLIES)	0.206***	0.164***	0.175***	0.200***	0.186***	0.777***	0.943***	0.939***	1		
CHANGE_LOG(ENGAGE)	0.113***	0.086***	0.094***	0.105***	0.112***	0.953***	0.742***	0.746***	0.727***	1	
RESPONSE	0.177***	0.283***	0.271***	0.209***	0.331***	0.062***	0.127***	0.116***	0.074***	0.168***	1

Panel B: Pearson Correlation between Key Variables for Tweet Firm-quarters

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
LOG(ENGAGEMENT)	1									
RESPONSE	0.294***	1								
CHANGE_LOG(LIKES)	0.202***	0.110***	1							
CHANGE_LOG(RETWEETS)	0.182***	0.102***	0.953***	1						
CHANGE_LOG(RETPLIES)	0.173***	0.052***	0.941***	0.933***	1					
CHANGE_LOG(ENGAGE)	0.093***	0.149***	0.734***	0.738***	0.717***	1				
UE_EARNINGS	0.019**	-0.015*	-0.005	-0.006	-0.004	-0.009	1			
SALES_GROWTH	-0.005	0.009	0.028***	0.031***	0.033***	0.017**	0.043***	1		
TOBINS'Q	0.131***	0.051***	0.016**	0.0115	0.008	-0.013*	-0.004	0.073***	1	
STOCK_RET_QTR	-0.018**	-0.007	0.025***	0.026***	0.020***	0.034***	0.049***	-0.005	0.148***	1

Panels A and B show the Pearson Coefficient between the Dependent Variables and Variables of Interest for the sub-sample comprising of only Tweet firm-quarters

All variables are as defined in Appendix A. *** p<0.01, ** p<0.05, * p<0.1

Table 3: Association between Stock Returns and Concurrent Change in Engagement Volume Variables – Base Model

	Dependent Variable = $EXCESS\_RETURN_{i,q,t}$				
	(1)	(2)	(3)	(4)	(5)
$CHANGE\_LOG(LIKES)_{i,q,t}$	**0.003*** **				
	(4.441)				
$CHANGE\_LOG(RETWEETS)_{i,q,t}$		**0.003*** **			
		(4.349)			
$CHANGE\_LOG(REPLIES)_{i,q,t}$			**0.003*** **		
			(3.822)		
$CHANGE\_LOG(ENGAGE)_{i,q,t}$				**0.003*** **	
				(3.843)	
$CHANGE\_RESPONSE_{i,q,t}$					0.001
					(1.151)
$LOG(NEWSPAPERS)_{i,q}$	-0.004**	-0.004**	-0.004**	-0.004**	-0.004**
	(-2.43)	(-2.439)	(-2.431)	(-2.426)	(-2.412)
$LOG(ANALYSTS)_{i,q}$	0.004*	0.004*	0.004*	0.004*	0.004*
	(1.896)	(1.889)	(1.905)	(1.89)	(1.914)
$INST_{i,q}$	-0.018***	-0.018***	-0.018***	-0.018***	-0.018***
	(-3.019)	(-3.02)	(-3.024)	(-3.017)	(-3.02)
$Q4_{i,q}$	0.009	0.009	0.009	0.009	0.009
	(1.44)	(1.437)	(1.445)	(1.435)	(1.43)
$LOSS_{i,q}$	-0.006***	-0.006***	-0.006***	-0.006***	-0.006***
	(-2.78)	(-2.785)	(-2.787)	(-2.785)	(-2.789)
$MKTR_{q,t}$	0.430**	0.431**	0.431**	0.429**	0.430**
	(2.357)	(2.361)	(2.366)	(2.356)	(2.36)
$SMB_{q,t}$	0.203	0.203	0.204	0.203	0.21
	(1.441)	(1.439)	(1.442)	(1.439)	(1.468)
$HML_{q,t}$	-0.148	-0.148	-0.149	-0.148	-0.15
	(-0.7)	(-0.701)	(-0.705)	(-0.703)	(-0.713)
$MOM_{q,t}$	-1.103***	-1.104***	-1.103***	-1.103***	-1.100***
	(-3.356)	(-3.359)	(-3.358)	(-3.356)	(-3.347)
$RMW_{q,t}$	-0.087	-0.087	-0.086	-0.087	-0.09
	(-1.049)	(-1.047)	(-1.044)	(-1.059)	(-1.093)
$CMA_{q,t}$	0.115	0.115	0.116	0.115	0.113
	(1.463)	(1.463)	(1.464)	(1.459)	(1.441)
CONSTANT	-0.027***	-0.027***	-0.027***	-0.027***	-0.027***
	(-2.962)	(-2.958)	(-2.962)	(-2.958)	(-2.976)
Observations	278,587	278,587	278,587	278,587	278,587
R-squared	0.146	0.146	0.146	0.146	0.147

Table 3 shows the results of a model similar to equation (2) of Bartov et al. (2018) for testing the association between contemporaneous change in engagement volume and the monthly excess stock returns testing the association between contemporaneous change in engagement volume and the monthly excess stock returns for the full sample (includes both Tweet as well as all non-Tweet firm- months).

The Table incorporates the Fama-French five-factor and Momentum factor as well and displays the results using Fama-MacBeth monthly cross-sectional regressions with Newey-West corrected standard errors for autocorrelation (two lags) used for calculating t-statistics. The reported slopes are computed as the time-series average of the slopes in monthly regressions of excess stock returns on the explanatory variables for the sample period 2006 - 2017 using the Model : $(R_{i,q,t} - Rf_{q,t}) = \Upsilon_0 + \Upsilon_1 CHANGE\_ENGAGEMENT\_VOLUME_{i,q,t} + \Upsilon_2 MOM_{q,t} + \Sigma\, \Upsilon_j FAMA\text{-}FRENCH\ FACTORS_{q,t} + \Sigma\, \Upsilon_k\, CONTROLS_{i,q,t} + \varepsilon_{i,q,t}$

where *i* indexes firm, *q* indexes quarter, and *t* indexes month.

Newey-West corrected t-statistics are in parentheses;*** p<0.01, ** p<0.05, * p<0.1; All variables are defined in Appendix A.

Table 4: Association between Stock Returns and Concurrent Change in Engagement Volume Variables

Panel A: Stock Returns and Concurrent Change in Engagement Volume Variables – All Firms

	Dependent Variable = *EXCESS_RETURN*$_{i,q,t}$				
	(1)	(2)	(3)	(4)	(5)
CHANGE_LOG(LIKES) $_{i,q,t}$	**0.003*** **				
	(3.619)				
CHANGE_LOG(RETWEETS)$_{i,q,t}$		**0.003*** **			
		(3.661)			
CHANGE_LOG(REPLIES)$_{i,q,t}$			**0.003*** **		
			(3.223)		
CHANGE_LOG(ENGAGE)$_{i,q,t}$				**0.002*** **	
				(3.479)	
CHANGE_RESPONSE$_{i,q,t}$					**0.003** **
					(2.386)
LOG(PRESSRELEASES)$_{i,q}$	0.036***	0.036***	0.036***	0.036***	0.036***
	(4.625)	(4.625)	(4.616)	(4.625)	(4.627)
LOG(NEWSPAPERS)$_{i,q}$	-0.006***	-0.006***	-0.006***	-0.006***	-0.006***
	(-3.583)	(-3.541)	(-3.549)	(-3.541)	(-3.404)
LOG(ANALYSTS)$_{i,q}$	0.001	0.001	0.001	0.001	0.001
	(0.831)	(0.81)	(0.834)	(0.806)	(0.763)
INS $_{i,q}$	-0.016***	-0.016***	-0.016***	-0.016***	-0.016***
	(-3.551)	(-3.567)	(-3.558)	(-3.551)	(-3.63)
Q4$_{i,q}$	0.007	0.007	0.007	0.007	0.007
	(1.555)	(1.552)	(1.549)	(1.555)	(1.562)
LOS $_{i,q}$	-0.003*	-0.003*	-0.003*	-0.003*	-0.003*
	(-1.761)	(-1.832)	(-1.79)	(-1.765)	(-1.853)
CHANGE_ANALYST_CONSENSUS$_{i,q,t}$	-0.008	-0.008	-0.008	-0.008	-0.008
	(-0.539)	(-0.534)	(-0.537)	(-0.53)	(-0.54)
NUM_RECO_UP$_{i,q,t}$	0.012***	0.012***	0.012***	0.012***	0.012***
	(10.274)	(10.337)	(10.358)	(10.232)	(9.946)
NUM_RECO_DOWN$_{i,q,t}$	-0.016***	-0.016***	-0.016***	-0.016***	-0.015***
	(-10.469)	(-10.454)	(-10.421)	(-10.418)	(-10.458)
UE_EARNINGS$_{i,q-1}$	0.346***	0.345***	0.343***	0.346***	0.342***
	(7.139)	(7.241)	(7.261)	(7.208)	(7.513)
MKTRF$_{q,t}$	0.314*	0.312*	0.314*	0.314*	0.324*
	(1.699)	(1.69)	(1.699)	(1.697)	(1.747)
SMB$_{q,t}$	0.197	0.203	0.201	0.199	0.202
	(1.421)	(1.439)	(1.432)	(1.424)	(1.432)
HML$_{q,t}$	-0.077	-0.074	-0.075	-0.077	-0.085
	(-0.396)	(-0.384)	(-0.388)	(-0.396)	(-0.447)
MOM$_{q,t}$	-1.035***	-1.036***	-1.036***	-1.035***	-1.024***

	(-3.424)	(-3.423)	(-3.426)	(-3.421)	(-3.376)
$RMW_{q,t}$	-0.036	-0.037	-0.036	-0.036	-0.044
	(-0.407)	(-0.417)	(-0.402)	(-0.405)	(-0.49)
$CMA_{q,t}$	0.077	0.079	0.078	0.078	0.072
	(1.05)	(1.066)	(1.058)	(1.059)	(0.998)
CONSTANT	-0.030***	-0.030***	-0.030***	-0.030***	-0.030***
	(-3.122)	(-3.116)	(-3.116)	(-3.123)	(-3.114)
Observations	207,965	207,965	207,965	207,965	207,965
R-squared	0.18	0.18	0.18	0.18	0.18

Panel B: Stock Returns and Concurrent Change in Engagement Volume Variables – Only Tweet Firms

	Dependent Variable = $EXCESS\_RETURN_{i,q,t}$				
	(1)	(2)	(3)	(4)	(5)
$CHANGE\_LOG(LIKES)_{i,q,t}$	**0.001***				
	(1.66)				
$CHANGE\_LOG(RETWEETS)_{i,q,t}$		**0.001***			
		(1.928)			
$CHANGE\_LOG(REPLIES)_{i,q,t}$			0.001		
			(1.261)		
$CHANGE\_LOG(ENGAGE)_{i,q,t}$				**0.001***	
				(1.66)	
$CHANGE\_RESPONSE_{i,q,t}$					0.001
					(1.226)
$LOG(PRESSRELEASES)_{i,q}$	0.007***	0.007***	0.006***	0.007***	0.006***
	(4.648)	(4.671)	(4.519)	(4.685)	(4.483)
$LOG(NEWSPAPERS)_{i,q}$	-0.002	-0.002	-0.002	-0.002	-0.002
	(-1.44)	(-1.358)	(-1.428)	(-1.415)	(-1.515)
$LOG(ANALYSTS_{i,q}$	-0.003**	-0.003**	-0.003**	-0.003**	-0.003**
	(-2.233)	(-2.272)	(-2.25)	(-2.219)	(-2.164)
$INST_{i,q}$	-0.001	-0.001	-0.001	-0.001	-0.002
	(-0.31)	(-0.318)	(-0.296)	(-0.319)	(-0.614)
$Q_{i,q}$	0.002	0.002	0.002	0.002	0.002
	(0.707)	(0.693)	(0.692)	(0.706)	(0.76)
$LOSS_{i,q}$	-0.011***	-0.011***	-0.011***	-0.011***	-0.011***
	(-5.85)	(-5.816)	(-5.832)	(-5.855)	(-5.827)
$CHANGE\_ANALYST\_CONSENSUS_{i,q,t}$	-0.023	-0.023	-0.023	-0.024	-0.024
	(-1)	(-0.986)	(-0.99)	(-0.991)	(-1.017)
$NUM\_RECO\_UP_{i,q,t}$	0.014***	0.014***	0.014***	0.014***	0.014***
	(9.19)	(9.198)	(9.257)	(9.154)	(9.131)
$NUM\_RECO\_DOWN_{i,q,t}$	-0.017***	-0.017***	-0.017***	-0.017***	-0.017***
	(-8.926)	(-8.876)	(-8.782)	(-8.882)	(-8.697)
$UE\_EARNINGS_{i,q-1}$	0.455***	0.441***	0.450***	0.450***	0.445***
	(5.242)	(5.35)	(5.34)	(5.267)	(5.214)
$MKTR_{q,t}$	0.222	0.22	0.222	0.221	0.241
	(1.336)	(1.315)	(1.331)	(1.324)	(1.476)
$SMB_{q,t}$	0.143	0.159	0.138	0.15	0.153
	(1.457)	(1.64)	(1.397)	(1.544)	(1.584)
$HML_{q,t}$	0.253	0.254	0.253	0.253	0.255
	(1.294)	(1.303)	(1.298)	(1.3)	(1.312)
$MOM_{q,t}$	-0.444**	-0.436**	-0.448**	-0.437**	-0.441**
	(-2.096)	(-2.082)	(-2.114)	(-2.084)	(-2.092)

$RMW_{q,t}$	0.018	0.014	0.027	0.019	0.02
	(0.171)	(0.135)	(0.238)	(0.175)	(0.177)
$CMA_{q,t}$	0.049	0.054	0.052	0.052	0.048
	(0.548)	(0.584)	(0.57)	(0.567)	(0.534)
CONSTANT	0.007**	0.007**	0.007**	0.006**	0.007**
	(2.241)	(2.257)	(2.295)	(2.214)	(2.314)
Observations	72,352	72,352	72,352	72,352	72,352
R-squared	0.155	0.155	0.155	0.155	0.155

Panel A shows the results of the Fama-French five-factor model for testing the association between contemporaneous change in engagement volume and the monthly excess stock returns for the full sample (includes both Tweet as well as all non-Tweet firm-months).

Panel B shows the results of the Fama-French five-factor model for testing the association between contemporaneous change in engagement volume and the monthly excess stock returns for a sub-sample of only tweet firm-months (includes only firms which have created a Twitter account and have started tweeting).

Both panels incorporate the Momentum factor as well and display the results using Fama-MacBeth monthly cross-sectional regressions with Newey-West corrected standard errors for autocorrelation (two lags) used for calculating t-statistics. The reported slopes are computed as the time-series average of the slopes in monthly regressions of excess stock returns on the explanatory variables for the sample period 2006 - 2017 using Model 1: $(R_{i,q,t} - Rf_{q,t}) = \Upsilon_0 + \Upsilon_1 CHANGE\_ENGAGEMENT\_VOLUME_{i,q,t} + \Upsilon_2 MOM_{q,t} + \Sigma \Upsilon_j FAMA\text{-}FRENCH\ FACTORS_{q,t} + \Sigma \Upsilon_k CONTROLS_{i,q,t} + \varepsilon_{i,q,t}$

where *i* indexes firm, *q* indexes quarter, and *t* indexes month.

Newey-West corrected t-statistics are in parentheses ;*** p<0.01, ** p<0.05, * p<0.1; All variables are defined in Appendix A.

Table 5: Association between Stock Returns and Lagged Change in Engagement Volume Variables – All Firms

Panel A: Association between Stock Returns and One Month Lagged Change in Engagement Volume Variables

	Dependent Variable = *EXCESS_RETURN*$_{i,q,t}$				
	(1)	(2)	(3)	(4)	(5)
CHANGE_LOG(LIKES) $_{i,q/q-1,t-1}$	**0.002*****				
	(2.959)				
CHANGE_LOG(RETWEETS) $_{i,q/q-1,t-1}$		**0.002*****			
		(2.763)			
CHANGE_LOG(REPLIES) $_{i,q/q-1,t-1}$			**0.003*****		
			(3.001)		
CHANGE_LOG(ENGAGE) $_{i,q/q-1,t-1}$				**0.002*****	
				(2.844)	
CHANGE_RESPONSE $_{i,q/q-1,t-1}$					0.001
					(0.736)
LOG(PRESSRELEASES)$_{i,q}$	0.036***	0.036***	0.036***	0.036***	0.036***
	(4.603)	(4.606)	(4.595)	(4.603)	(4.614)
LOG(NEWSPAPERS)$_{i,q}$	-0.006***	-0.006***	-0.006***	-0.006***	-0.006***
	(-3.561)	(-3.538)	(-3.532)	(-3.552)	(-3.574)
LOG(ANALYSTS)$_{i,q}$	0.001	0.001	0.001	0.001	0.001
	(0.885)	(0.869)	(0.866)	(0.872)	(0.878)
INST$_{i,q}$	-0.016***	-0.016***	-0.016***	-0.016***	-0.016***
	(-3.585)	(-3.595)	(-3.592)	(-3.58)	(-3.563)
Q4$_{i,q}$	0.007	0.007	0.007	0.007	0.007
	(1.557)	(1.558)	(1.556)	(1.556)	(1.55)
LOSS$_{i,q}$	-0.003*	-0.003*	-0.003*	-0.003*	-0.003*
	(-1.834)	(-1.845)	(-1.832)	(-1.842)	(-1.703)
CHANGE_ANALYST_CONSENSUS$_{i,q,t}$	-0.008	-0.007	-0.007	-0.007	-0.008
	(-0.532)	(-0.518)	(-0.488)	(-0.519)	(-0.55)
NUM_RECO_UP$_{i,q,t}$	0.012***	0.012***	0.012***	0.012***	0.012***
	(10.629)	(10.546)	(10.741)	(10.621)	(10.611)
NUM_RECO_DOWN$_{i,q,t}$	-0.016***	-0.016***	-0.015***	-0.016***	-0.015***
	(-10.456)	(-10.443)	(-10.416)	(-10.447)	(-10.572)
UE_EARNINGS$_{i,q-1}$	0.340***	0.340***	0.339***	0.340***	0.348***
	(7.396)	(7.406)	(7.371)	(7.377)	(7.026)
MKTRF$_{q,t}$	0.315*	0.314*	0.316*	0.314*	0.309*
	(1.704)	(1.695)	(1.707)	(1.699)	(1.671)
SMB$_{q,t}$	0.203	0.205	0.202	0.204	0.206
	(1.444)	(1.446)	(1.437)	(1.443)	(1.45)

$HML_{q,t}$	-0.072	-0.073	-0.073	-0.072	-0.072
	(-0.372)	(-0.376)	(-0.379)	(-0.372)	(-0.369)
$MOM_{q,t}$	-1.036***	-1.036***	-1.036***	-1.037***	-1.038***
	(-3.428)	(-3.425)	(-3.426)	(-3.429)	(-3.435)
$RMW_{q,t}$	-0.039	-0.038	-0.038	-0.038	-0.034
	(-0.435)	(-0.429)	(-0.428)	(-0.43)	(-0.386)
$CMA_{q,t}$	0.077	0.078	0.078	0.078	0.077
	(1.051)	(1.056)	(1.063)	(1.054)	(1.048)
CONSTANT	-0.030***	-0.030***	-0.030***	-0.030***	-0.030***
	(-3.112)	(-3.11)	(-3.103)	(-3.112)	(-3.115)
Observations	207,965	207,965	207,965	207,965	207,965
R-squared	0.18	0.18	0.18	0.18	0.18

Panel B: Association between Stock Returns and Two Months Lagged Change in Engagement Volume Variables

	Dependent Variable = $EXCESS\_RETURN_{i,q,t}$				
VARIABLES	(1)	(2)	(3)	(4)	(5)
$CHANGE\_LOG(LIKES)_{i,q/q-1,t-2}$	0.001				
	(1.481)				
$CHANGE\_LOG(RETWEETS)_{i,q/q-1,t-2}$		0.001			
		(1.123)			
$CHANGE\_LOG(REPLIES)_{i,q/q-1,t-2}$			0.001		
			(1.104)		
$CHANGE\_LOG(ENGAGE)_{i,q/q-1,t-2}$				0.001	
				(1.365)	
$CHANGE\_RESPONSE_{i,q/q-1,t-2}$					0.001
					(0.768)
$LOG(PRESSRELEASES)_{i,q}$	0.036***	0.036***	0.036***	0.036***	0.036***
	(4.628)	(4.641)	(4.641)	(4.623)	(4.587)
$LOG(NEWSPAPERS)_{i,q}$	-0.006***	-0.006***	-0.006***	-0.006***	-0.006***
	(-3.619)	(-3.658)	(-3.637)	(-3.631)	(-3.484)
$LOG(ANALYSTS)_{i,q}$	0.001	0.001	0.001	0.001	0.001
	(0.91)	(0.923)	(0.818)	(0.921)	(1.004)
$INST_{i,q}$	-0.016***	-0.016***	-0.016***	-0.016***	-0.016***
	(-3.558)	(-3.546)	(-3.463)	(-3.548)	(-3.587)
$Q4_{i,q}$	0.007	0.007	0.007	0.007	0.007
	(1.54)	(1.534)	(1.531)	(1.537)	(1.551)
$LOSS_{i,q}$	-0.003*	-0.003*	-0.003*	-0.003	-0.003*
	(-1.716)	(-1.664)	(-1.685)	(-1.627)	(-1.822)
$CHANGE\_ANALYST\_CONSENSUS_{i,q,t}$	-0.009	-0.008	-0.008	-0.009	-0.003
	(-0.571)	(-0.538)	(-0.549)	(-0.578)	(-0.289)
$NUM\_RECO\_UP_{i,q,t}$	0.012***	0.012***	0.012***	0.012***	0.012***
	(10.739)	(11.089)	(10.985)	(10.827)	(10.504)
$NUM\_RECO\_DOWN_{i,q,t}$	-0.016***	-0.016***	-0.015***	-0.016***	-0.016***
	(-10.471)	(-10.475)	(-10.387)	(-10.478)	(-10.494)
$UE\_EARNINGS_{i,q-1}$	0.320***	0.315***	0.330***	0.322***	0.328***
	(7.548)	(7.34)	(7.667)	(7.596)	(7.519)
$MKTRF_{q,t}$	0.331*	0.330*	0.326*	0.332*	0.320*
	(1.766)	(1.765)	(1.748)	(1.771)	(1.718)
$SMB_{q,t}$	0.23	0.234	0.218	0.23	0.222
	(1.492)	(1.496)	(1.479)	(1.492)	(1.483)
$HML_{q,t}$	-0.084	-0.085	-0.081	-0.085	-0.073
	(-0.441)	(-0.447)	(-0.421)	(-0.444)	(-0.373)
$MOM_{q,t}$	-1.011***	-1.007***	-1.023***	-1.010***	-1.038***

	(-3.31)	(-3.288)	(-3.37)	(-3.309)	(-3.433)
$RMW_{q,t}$	-0.037	-0.036	-0.033	-0.035	-0.038
	(-0.421)	(-0.403)	(-0.37)	(-0.397)	(-0.433)
$CMA_{q,t}$	0.07	0.069	0.072	0.068	0.074
	(0.977)	(0.966)	(1)	(0.954)	(1.012)
CONSTANT	-0.030***	-0.030***	-0.030***	-0.030***	-0.030***
	(-3.165)	(-3.185)	(-3.162)	(-3.167)	(-3.144)
Observations	207,965	207,965	207,965	207,965	207,965
R-squared	0.18	0.18	0.18	0.18	0.18

Table 5 shows the results of the Fama-French five-factor model for testing the association between lagged change in engagement volume and the monthly excess stock returns for the full sample (includes both Tweet as well as all non-Tweet firm- months). Panel A has the results for one-month lagged and Panel B for two-month lagged variables.

The table incorporates the Momentum factor as well and displays the results using Fama-MacBeth monthly cross-sectional regressions with Newey-West corrected standard errors for autocorrelation (two lags) used for calculating t-statistics. The reported slopes are computed as the time-series average of the slopes in monthly regressions of excess stock returns on the explanatory variables for the sample period 2006 - 2017 using Model 1: $(R_{i,q,t} - Rf_{q,t}) = \Upsilon_0 + \Upsilon_1 CHANGE\_ENGAGEMENT\_VOLUME_{i,q,t-1/2} + \Upsilon_2 MOM_{q,t} + \Sigma\, \Upsilon_j FAMA\text{-}FRENCH\ FACTORS_{q,t} + \Sigma\, \Upsilon_k\, CONTROLS_{i,q,t} + \varepsilon_{i,q,t}$

where *i* indexes firm, *q* indexes quarter, and *t* indexes month.

Newey-West corrected t-statistics are in parentheses;*** p<0.01, ** p<0.05, * p<0.1; All variables are defined in Appendix A.

Table 6: Association between Firm Value and Engagement Volume Variables – All Firms

	Dependent Variable = *TOBINS'Q$_{i,q}$*				
	(1)	(2)	(3)	(4)	(5)
LOG(LIKES)$_{i,q}$	**0.011***				
	(1.955)				
LOG(RETWEETS)$_{i,q}$		**0.009***			
		(1.645)			
LOG(REPLIES)$_{i,q}$			0.01		
			(1.613)		
LOG(ENGAGEMENT)$_{i,q}$				**0.008***	
				(1.65)	
RESPONSE$_{i,q}$					0.019
					(1.065)
LOG(ASSETS)$_{i,q}$	-0.692***	-0.682***	-0.682***	-0.682***	-0.682***
	(-20.784)	(-20.71)	(-20.706)	(-20.706)	(-20.671)
ROA$_{i,q}$	-1.131***	-2.066***	-2.066***	-2.066***	-2.067***
	(-5.069)	(-8.302)	(-8.303)	(-8.303)	(-8.3)
ROA$_{i,q-1}$	0.145	0.078	0.078	0.077	0.078
	(0.759)	(0.41)	(0.41)	(0.409)	(0.411)
LEVERAGE$_{i,q}$	0	0.001	0.001	0.001	0.001
	(0.026)	(0.314)	(0.316)	(0.315)	(0.332)
LOG(PRESSRELEASES)$_{i,q}$	0.229***	0.227***	0.228***	0.227***	0.231***
	(10.075)	(10.08)	(10.095)	(10.073)	(10.152)
LOG(NEWSPAPERS)$_{i,q}$	0.394***	0.392***	0.392***	0.392***	0.392***
	(19.178)	(19.209)	(19.209)	(19.21)	(19.21)
ACQUISITION$_{i,q}$	-0.064**	-0.063**	-0.063**	-0.063**	-0.063**
	(-2.183)	(-2.189)	(-2.186)	(-2.192)	(-2.19)
LOSS$_{i,q}$		-0.306***	-0.306***	-0.306***	-0.307***
		(-17.973)	(-17.972)	(-17.972)	(-17.977)
CONSTANT	6.596***	6.615***	6.614***	6.614***	6.612***
	(32.388)	(32.697)	(32.692)	(32.693)	(32.645)
Observations	163,196	163,196	163,196	163,196	163,196
R-squared	0.734	0.736	0.736	0.736	0.736
Year-qtr Fixed-Effects	Yes	Yes	Yes	Yes	Yes
Firm Fixed-Effects	Yes	Yes	Yes	Yes	Yes
Clustering of Errors	Firm	Firm	Firm	Firm	Firm

Table 6 shows the results of the association between engagement volume and the firm's market value using OLS regression for the full sample (includes both Tweet as well as all non-Tweet firm- quarters) for the period 2006 – 2017. The Model used is: $TOBINS'Q_{i,q} = \beta_0 + \beta_1 ENGAGEMENT\_VOLUME_{i,q} + \Sigma\beta_J CONTROLS_{i,q} + YEAR\_QTR\ FIXED\text{-}EFFECTS + FIRM\ FIXED\text{-}EFFECTS + \varepsilon_{i,q}$

where *i* indexes firm and *q* indexes quarter.

Robust t statistics are in parentheses; *** p<0.01, ** p<0.05, * p<0.1; All variables are defined in Appendix A.

Table 7: Association between Sales Growth and Engagement Volume Variables – All Firms

	Dependent Variable = $SALES\_GROWTH_{i,q}$				
	(1)	(2)	(3)	(4)	(5)
$CHANGE\_LOG(LIKES)_{i,q}$	**0.006*** **				
	(3.275)				
$CHANGE\_LOG(RETWEETS)_{i,q}$		**0.006*** **			
		(3.393)			
$CHANGE\_LOG(REPLIES)_{i,q}$			**0.006*** **		
			(3.264)		
$CHANGE\_LOG(ENGAGE)_{i,q}$				**0.003** **	
				(2.347)	
$CHANGE\_RESPONSE_{i,q}$					-0.013
					(-1.551)
$LOG(ASSETS)_{i,q}$	0.202***	0.202***	0.202***	0.202***	0.202***
	(25.935)	(25.936)	(25.935)	(25.933)	(25.935)
$MTB_{i,q}$	0.002***	0.002***	0.002***	0.002***	0.002***
	(5.311)	(5.311)	(5.313)	(5.312)	(5.315)
$LOG(NUM\_ANALYSTS)_{i,q}$	-0.005*	-0.005*	-0.005*	-0.005*	-0.005*
	(-1.766)	(-1.767)	(-1.767)	(-1.752)	(-1.757)
$LOG(PRESSRELEASES)_{i,q}$	0.005***	0.005***	0.005***	0.005***	0.005***
	(3.177)	(3.19)	(3.199)	(3.197)	(3.206)
$LOG(NEWSPAPERS)_{i,q}$	0.008***	0.008***	0.008***	0.008***	0.008***
	(5.112)	(5.111)	(5.116)	(5.127)	(5.147)
$LOG(SALES)_{i,q-1}$	-0.272***	-0.272***	-0.272***	-0.272***	-0.272***
	(-28.658)	(-28.659)	(-28.658)	(-28.657)	(-28.654)
$SALES\_GROWTH_{i,q-1}$	-0.123***	-0.123***	-0.123***	-0.123***	-0.123***
	(-14.631)	(-14.629)	(-14.63)	(-14.63)	(-14.627)
$ADV\_EXP\_QTR_{i,q}$	4.068***	4.067***	4.067***	4.069***	4.072***
	(7.436)	(7.434)	(7.433)	(7.436)	(7.438)
$CHG\_BACKLOG_{i,q}$	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(-5.033)	(-5.034)	(-5.033)	(-5.035)	(-5.033)
CONSTANT	-0.028	-0.028	-0.028	-0.028	-0.028
	(-1.035)	(-1.035)	(-1.036)	(-1.036)	(-1.043)
Observations	132,885	132,885	132,885	132,885	132,885
R-squared	0.243	0.243	0.243	0.243	0.243
Year-qtr Fixed-Effects	Yes	Yes	Yes	Yes	Yes
Firm Fixed-Effects	Yes	Yes	Yes	Yes	Yes
Clustering of Errors	Firm	Firm	Firm	Firm	Firm

Table 7 shows the results of testing the association between engagement volume and sales growth OLS regression for the full sample (includes both Tweet as well as all non-Tweet firm- quarters) for the period 2006 – 2017.The Model used is: $SALES\_GROWTH_{i,q} = \beta_0 + \beta_1 CHANGE\_ENGAGEMENT\_VOLUME_{i,q} + \Sigma\beta_J CONTROLS_{i,q} + YEAR\_QTR\ FIXED\text{-}EFFECTS + FIRM\ FIXED\text{-}EFFECTS + \varepsilon_{i,q}$

where i indexes firm and q indexes quarter.

Robust t statistics are in parentheses; *** p<0.01, ** p<0.05, * p<0.1; All variables are as defined in Appendix A.

Table 8: Stock Returns and Engagement Volume Variables – Additional Analysis

Panel A: Stock Returns and Concurrent Change in Engagement Volume Variables – All Firms (excluding the month of Earnings Announcement)

	Dependent Variable = $EXCESS\_RETURN_{i,q,t}$				
	(1)	(2)	(3)	(4)	(5)
$CHANGE\_LOG(LIKES)_{i,q,t}$	**0.003*** **				
	(3.645)				
$CHANGE\_LOG(RETWEETS)_{i,q,t}$		**0.003*** **			
		(3.676)			
$CHANGE\_LOG(REPLIES)_{i,q,t}$			**0.003*** **		
			(3.261)		
$CHANGE\_LOG(ENGAGE)_{i,q,t}$				**0.002*** **	
				(3.71)	
$CHANGE\_RESPONSE_{i,q,t}$					**0.004** **
					(2.483)
$LOG(PRESSRELEASES)_{i,q}$	0.035***	0.035***	0.035***	0.035***	0.035***
	(4.598)	(4.586)	(4.589)	(4.592)	(4.604)
$LOG(NEWSPAPERS)_{i,q}$	-0.006***	-0.006***	-0.006***	-0.006***	-0.006***
	(-3.671)	(-3.544)	(-3.575)	(-3.576)	(-3.518)
$LOG(ANALYSTS)_{i,q}$	0.003*	0.003*	0.003*	0.003*	0.003*
	(1.802)	(1.768)	(1.782)	(1.758)	(1.736)
$INST_{i,q}$	-0.019***	-0.019***	-0.019***	-0.019***	-0.018***
	(-3.851)	(-3.857)	(-3.864)	(-3.845)	(-3.874)
$Q4_{i,q}$	0.007	0.007	0.007	0.007	0.007
	(1.577)	(1.574)	(1.568)	(1.576)	(1.575)
$LOSS_{i,q}$	-0.003	-0.003	-0.003	-0.003	-0.003
	(-1.349)	(-1.383)	(-1.415)	(-1.321)	(-1.592)
$CHANGE\_ANALYST\_CONSENSUS_{i,q,t}$	-0.018	-0.016	-0.018	-0.016	-0.023
	(-0.778)	(-0.752)	(-0.77)	(-0.746)	(-0.817)
$NUM\_RECO\_UP_{i,q,t}$	0.012***	0.012***	0.012***	0.012***	0.012***
	(7.985)	(8.394)	(8.004)	(8.148)	(7.473)
$NUM\_RECO\_DOWN_{i,q,t}$	-0.016***	-0.016***	-0.016***	-0.016***	-0.016***
	(-10.209)	(-10.2)	(-10.17)	(-10.103)	(-10.419)
$UE\_EARNINGS_{i,q-1}$	0.220***	0.220***	0.215***	0.222***	0.204***
	(4.424)	(4.451)	(4.291)	(4.506)	(3.998)
$MKTRF_{q,t}$	0.206	0.201	0.206	0.204	0.212
	(1.155)	(1.134)	(1.156)	(1.147)	(1.184)
$SMB_{q,t}$	0.24	0.237	0.236	0.232	0.248
	(1.353)	(1.358)	(1.356)	(1.349)	(1.364)

$HML_{q,t}$	-0.122	-0.118	-0.117	-0.122	-0.119
	(-0.67)	(-0.644)	(-0.638)	(-0.672)	(-0.648)
$MOM_{q,t}$	-0.843***	-0.850***	-0.852***	-0.848***	-0.846***
	(-3.03)	(-3.075)	(-3.086)	(-3.059)	(-3.048)
$RMW_{q,t}$	-0.097	-0.095	-0.093	-0.093	-0.105
	(-1.103)	(-1.083)	(-1.064)	(-1.07)	(-1.169)
$CMA_{q,t}$	0.064	0.067	0.067	0.067	0.061
	(0.937)	(0.973)	(0.965)	(0.965)	(0.896)
CONSTANT	-0.031***	-0.031***	-0.031***	-0.031***	-0.031***
	(-3.237)	(-3.221)	(-3.225)	(-3.225)	(-3.24)
Observations	169,174	169,174	169,174	169,174	169,174
R-squared	0.182	0.182	0.182	0.182	0.182

Panel B: Three-Day CAR and Change in Engagement Volume around Earnings Announcement

	Dependent Variable = $CAR_{i,q,t}$ [-1;+1]					
	(1)	(2)	(3)	(4)	(5)	(6)
$CHANGE\_LOG(ENGAGE)_{i,q,t}$	0.000					
	(0.815)					
$CHANGE\_LOG(ENGAGE)_{i,q/q-1,,t-1}$		0.000				
		(0.546)				
$CHANGE\_LOG(ENGAGE)_{i,q/q-1,,t-2}$			0.000			
			(0.204)			
$CHANGE\_RESPONSE_{i,q.t}$				0.001		
				(1.436)		
$CHANGE\_RESPONSE_{i,q,t-1}$					0.000	
					(0.322)	
$CHANGE\_RESPONSE_{i,q,t-2}$						-0.001
						(-0.583)
$UE\_EARNINGS_{i,q}$	0.329***	0.329***	0.330***	0.329***	0.329***	0.330***
	(42.032)	(41.954)	(41.939)	(42.035)	(41.952)	(41.937)
CONSTANT	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
	(6.887)	(7.012)	(6.911)	(6.911)	(6.961)	(6.994)
Observations	118,320	117,847	117,321	118,320	117,847	117,321
R-squared	0.015	0.015	0.015	0.015	0.015	0.015

Panel A shows the results of the Fama-French five-factor model for testing the association between contemporaneous change in engagement volume and the monthly excess stock returns for the full sample (includes both Tweet as well as all non-Tweet firm-months) but excluding the month of the earnings announcement.

The panel incorporates the Momentum factor as well and displays the results using Fama-MacBeth monthly cross-sectional regressions with Newey-West corrected standard errors for autocorrelation (two lags) used for calculating t-statistics. The reported slopes are computed as the time-series average of the slopes in monthly regressions of excess stock returns on the explanatory variables for the sample period 2006 - 2017 using Model 1: $(R_{i,q,t} - Rf_{q,t}) = \Upsilon_0 + \Upsilon_1 CHANGE\_ENGAGEMENT\_VOLUME_{i,q,t} + \Upsilon_2 MOM_{q,t} + \Sigma\, \Upsilon_j FAMA\text{-}FRENCH\ FACTORS_{q,t} + \Sigma\, \Upsilon_k\, CONTROLS_{i,q,t} + \varepsilon_{i,q,t}$

where *i* indexes firm, *q* indexes quarter, and *t* indexes month.

Newey-West corrected t-statistics are in parentheses;*** p<0.01, ** p<0.05, * p<0.1; All variables are defined in Appendix A.

Panel B shows the results of testing the association between change in lagged engagement volume and the 3-day Cumulative Abnormal Return [-1;+1] around the Earnings announcement date for the full sample (includes both Tweet as well as all non-Tweet firm- quarters) using the Model: $CAR_{i,q,t}$ [-1; +1]= $\beta_0 + \beta_1 CHANGE\_ENGAGEMENT\_VOLUME_{i,q/q-1,t/t-1/t-2} + \beta_2\ UE\_EARNINGS_{i,q} + \varepsilon_{i,q,,t}$

where *i* indexes firm, *q* indexes quarter, and *t* indexes month.

Robust t statistics are in parentheses; *** p<0.01, ** p<0.05, * p<0.1; All variables are as defined in Appendix A.

Table 9: Stock Returns and Engagement Volume Variables – Robustness Tests

Panel A: Stock Returns and Change in Engagement Volume Variables - Tweets from Primary and Secondary Twitter Accounts (All Firms)

	Dependent Variable = $EXCESS\_RETURN_{i,q,t}$			
	(1)	(2)	(3)	(4)
$CHANGE\_LOG(LIKES)_{i,q,t}$	**0.003*** **			
	(4.175)			
$CHANGE\_LOG(RETWEETS)_{i,q,t}$		**0.003*** **		
		(4.221)		
$CHANGE\_LOG(REPLIES)_{i,q,t}$			**0.003*** **	
			(3.512)	
$CHANGE\_LOG(ENGAGE)_{i,q,t}$				**0.002*** **
				(4.107)
Observations	207,965	207,965	207,965	207,965
R-squared	0.14	0.14	0.14	0.14
Fama-French Factors	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Panel B: Stock Returns and Industry-Adjusted Engagement Variables - (All Firms)

	Dependent Variable = $EXCESS\_RETURN_{i,q,t}$	
	(1)	(2)
$CHANGE\_LOG(ENGAGE)\_IND\_ADJ_{i,q,t}$	**0.003*** **	
	(3.236)	
$CHANGE\_RESPONSE\_IND\_ADJ_{i,q,t}$		**0.003** **
		(2.399)
Observations	207,965	207,965
R-squared	0.18	0.18
Fama-French Factors	Yes	Yes
Controls	Yes	Yes

Panel A shows the results of the Fama-French five-factor model for testing the association between change in engagement volume and the monthly excess stock returns for the full sample (includes both Tweet as well as all non-Tweet firm- months). The tweets are from both the Primary as well as Secondary Twitter accounts of a firm.

Panel B shows the results of the Fama-French five-factor model for testing the association between SIC-2 digit Industry-adjusted engagement volume variables and the monthly excess stock returns for the full sample (includes both Tweet as well as all non-Tweet firm- months). The tweets are from only the Primary Twitter accounts of a firm.

Both the Panels incorporate the Momentum factor as well and display the results using Fama-MacBeth monthly cross-sectional regressions with Newey-West corrected standard errors for autocorrelation (two lags) used for calculating t-statistics. The reported slopes are computed as the time-series average of the slopes in monthly regressions of excess stock returns on the explanatory variables for the sample period 2006 - 2017 using the Model 1: $(R_{i,q,t} - Rf_{q,t}) = \Upsilon_0 + \Upsilon_1 CHANGE\_ENGAGEMENT\_VOLUME_{i,q,t} + \Upsilon_2 MOM_{q,t} + \Sigma\, \Upsilon_j FAMA\text{-}FRENCH\ FACTORS_{q,t} + \Sigma\, \Upsilon_k\, CONTROLS_{i,q,t} + \varepsilon_{i,q,t}$

where *i* indexes the firm, *q* indexes quarter, and *t* indexes month.

Newey-West corrected t-statistics are in parentheses;*** p<0.01, ** p<0.05, * p<0.1; All variables are defined in Appendix A.