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The Effect of Twitter Dissemination on Cost of Equity: A Big Data Approach

Abstract

Reducing information asymmetry between investors and a firm can have an impact on the cost of equity, especially in an environment or times of uncertainty. New technologies can potentially help disseminate corporate financial information, reducing such asymmetries. In this paper we analyse firms' dissemination decisions using Twitter, developing a comprehensive measure of the amount of financial information that a company makes available to investors (*iDisc*) from a big data of firms' tweets (1,197,208 tweets). Using a sample of 4,131 firm-year observations for 791 non-financial firms listed on the US NASDAQ stock exchange over the period 2009-2015, we find evidence that *iDisc* significantly reduces the cost of equity. These results are pronounced for less visible firms which are relatively small in size, have a low analyst following and a small number of investors. Highly visible firms are less likely to benefit from *iDisc* in influencing their cost of equity as other communication channels may have widely disseminated their financial information. Our investigations encourage managers to consider the benefits of directly spreading a firm's financial information to stakeholders and potential investors using social media in order to reduce firm equity premium (COE).

Keywords

Big data; Twitter; Dissemination; Disclosure; Cost of equity

1. Introduction

Revolutionary communication tools, such as social media applications, provide a massive amount of information ("*big data*"), which leads to a great deal of attention and action on the part of firms (de Camargo Fiorini, Seles, Jabbour, Mariano, & de Sousa Jabbour, 2018). These tools of *big data* bring profound changes in the way that firms manage their customers and business (see Raguseo, 2018), and have become important channels to diffuse information (Agarwal, Kumar & Goel, 2019), as part of firms' disclosure strategy to meet the increased demand for information by investors. A key objective is to reduce the uncertainty about current and future investment opportunities. Corporate disclosure can help to reduce the information asymmetry that exists between management and market participants, and between informed and uninformed investors (Diamond & Verrecchia, 1991; O. Kim & Verrecchia, 1994; Leuz & Verrecchia, 2000). In turn, this can have significant implications as to which companies attract the necessary financial resources to grow and become successful.

Although corporate information is assumed to be available to all market participants once firms disclose, "*most firms have difficulty ensuring their news reaches a broad set of investors*", which results in information asymmetry (Blankespoor, Miller, & White, 2014, p. 80) and this increases the need for a better dissemination strategy. This strategy is about a firm's decision to spread information about the firm to the public through specific channels or not. A firm's decision to disseminate is different from its voluntary disclosure decision, which focuses more on providing information, if the benefits of disclosure outweigh the associated processing and proprietary costs (Kothari, Shu, & Wysocki, 2009b). Dissemination is also necessary for informing investors about a firm, resulting in improving investor recognition of the stock and therefore a lower cost of equity (hereafter, COE) (Merton, 1987). The challenge is that investors can only spend limited time and pay little attention to news about firms, due to the acquisition cost that they bear through searching, retrieving and understanding the required information (Hirshleifer, Lim, & Teoh, 2011; Hirshleifer & Teoh, 2003; Hong & Stein, 1999; Merton, 1987). As such, investors may rely on few information intermediaries, such as the press, to receive news about firms. Due to limitations in coverage, there is a high chance that investors will not receive the news about lower press coverage firms or start-ups that do not command the necessary recognition. Instead, managers may use social media as a complementary channel to address this challenge (Blankespoor et al., 2014). This makes it possible for investors to obtain relevant information on a timely basis and in doing so to reduce the acquisition cost of information, by saving the time and energy needed to search for relevant news. Such dissemination activity is expected to lead to lower information asymmetry and improve investor recognition. Therefore, our study seeks to examine whether a firm's dissemination of financial information (*iDisc*) on Twitter has an impact on the firm’s COE.

The effect of dissemination decisions has not been widely explored in the literature due to the difficulty of isolating dissemination from disclosure. Prior studies (Kimbrough & Louis, 2011; Mayew, 2008) have been either silent about the dissemination role or assume that dissemination exists once the disclosure is released. Although recent studies (Bushee, Core, Guay, & Hamm, 2010; E. X. Li, Ramesh, & Shen, 2011) have pointed out that dissemination can be isolated from disclosure through press coverage, firms have no control over the content and dissemination decision of the press. The press is also likely to adjust the content of information by expressing opinions, including summaries, or providing additional information, which makes the effect of dissemination unclear. Conversely, firms may opt to use Twitter for dissemination as they can have full control over the volume, frequency and timing of the disseminated information and can reach investors undiluted. However, there is little empirical evidence on how firms' dissemination of financial information on Twitter can be valuable to firms. Hence, this study aims to shed light on whether *iDisc* affects their COE, also controlling for many relevant factors.

By meeting our objectives, we show that firms can reduce the COE by improving their information environment through their dissemination activities on *big data* information technologies channels. This evidence suggests that the managerial choice of using *iDisc* and diffusing information through their social media accounts could be perceived as part of the firm’s strategic voluntary disclosure policy. This finding also shows the importance of using Twitter as a communication channel to connect with market participants, to reduce investors’ acquisition costs, reduce the gap between informed and uninformed investors and help investors to make better investment decisions. This paper contributes to the growing literature on the market consequences of firms’ dissemination of information on Twitter (Blankespoor et al., 2014; Prokofieva, 2015; Lee et al., 2015; Jung et al., 2017; Mazboudi & Khalil, 2017). These studies show how firms benefit from Twitter activity by improving market liquidity and attenuating negative market reaction. First, we show how *iDisc* affects the implied COE, based on an average of four measures of COE. Our study adds to Al Guindy (2016), which examined firms’ use of Twitter and the cost of capital. We have examined the dissemination effect, which is different from firms’ decisions to use Twitter. We have also used dissimilar COE estimates, more control variables and a different estimation model. In addition, our study contributes to previous studies by focusing on firms that are traded on the NASDAQ stock exchange and by selecting a longer sample period. Second, while previous studies examined the effect of the level and quality of a variety of disclosure information and channels (Botosan, 1997; Orens, Aerts, & Cormier, 2010; El Ghoul, Guedhami, Kwok, & Mishra, 2011; Mangena, Li, & Tauringana 2016), our empirical settings focus on firms' dissemination activity. Our results show that dissemination has a meaningful effect on COE, which is not in line with prior studies (Hughes et al., 2007; Lambert et al., 2007, 2011) that argue that the real effect is from the information precision. Although tweets are short messages which are expected to have a smaller amount of information than an annual report, our results show the influence of *iDisc* on COE. Third, we contribute to previous studies (Blankespoor et al., 2014; Jung et al., 2017) that isolate the effect of dissemination from disclosure by examining the influence of dissemination on the COE. Fourth, the findings remain unchanged under varied news magnitudes and contents. Therefore, we extend the prior evidence of Kothari et al. (2009a) by examining the effect of dissemination and the tone of a new information intermediary, Twitter, and big data on the COE. Finally, we contribute to the literature on big data (e.g. Sivarajah, Kamal, Irani, & Weerakkody, 2017; Stieglitz, Mirbabaie, Ross, & Neuberger, 2018; Warren Jr, Moffitt, & Byrnes, 2015) by collecting over a million pieces of data for a longitudinal time period and constructing a measure of the amount of financial information that firms diffuse from the large set of firms’ tweets data. While some studies focus on outside and within firm data (e.g. Gandomi & Haider, 2015), our study focuses on the firm’s initiative data on Twitter. Overall, this study contributes to the literature by analyzing social media big data in the financial context.

The next section reviews the relevant literature. The methodology section outlines the sample data and model tested. The paper then presents and discusses the empirical results, comparing and contrasting them with past literature. The paper concludes by considering the theoretical and managerial implications of the empirical evidence.

2. Literature review and hypothesis development

2.1 Information asymmetry, information intermediaries and cost of equity

Cost of equity is the cost to a firm of using investors’ funds that the company raises and uses. Previous studies have documented the important role of accounting information in reducing a firm’s COE (Beyer, Cohen, Lys, & Walther, 2010; Easley & O'hara, 2004). Some attention has been paid to the communication channel used for disseminating firm information and its implications for the COE. Francis, Nanda, and Olsson (2008) show that disclosing management forecasts and conference calls are associated with a higher COE, whereas this association is not significant for press releases. Kothari et al. (2009) highlight the role of information intermediaries on the COE, finding that it is affected by business press coverage for both good and bad news. They find that information reported by management and analysts does not provide significant evidence. They also suggest that "*technological innovation […] and changes in disclosure channels and the number and type of information intermediaries that continue to reshape disclosure and financial reporting practices create new and exciting opportunities for research*" (p. 1667). Such intermediaries create value by being easier to manage, and being more efficient and specialised than other media channels (del Águila-Obra, Padilla-Meléndez, & Serarols-Tarres, 2007).

As "*the cost of equity capital is increasing in the level of information asymmetry*" (Beyer et al., 2010, p. 314), making dissemination decisions to spread information through different communication channels matters (Drake, Guest, & Twedt, 2014; Twedt, 2016). In essence, firms' dependence on financial intermediaries, such as the press, could be subject to some limitation as the press may favour articles about firms that attract a wider audience (Miller, 2006), which may affect the effectiveness of the firm's disclosure. Therefore, improving the reach and spread of information through dissemination could play a role in enhancing the usefulness of corporate disclosure. That is, different degrees of dissemination, apart from voluntary disclosure, matter (Drake et al., 2014). Previous studies have found that the dissemination level of the business press affects stock prices (E. X. Li et al., 2011), price discovery (Twedt, 2016), information asymmetry (Bushee et al., 2010) and the expected rate of return (Fang & Peress, 2009). Overall, these findings imply that dissemination has its own capital market consequences apart from disclosure.

2.2 Social media and financial dissemination

Social media employ mobile technologies and web-based to create highly interactive platforms by which various stakeholders, individuals and communities can create big data by sharing, discussing, co-creating, and modifying user-generated content (e.g. Shiau, Dwivedi, & Yang, 2017; Kietzmann, Hermkens, McCarthy, & Silvestre, 2011; Ngai, Tao, & Moon, 2015). In addition to being user-driven communities, over the past years social media channels have provided an enormous amount of timely data that has served many business functions and purposes (Manika, Papagiannidis, & Bourlakis, 2013). When it comes to financial dissemination, firms attempt to improve the information environment by initiating investor relations (IR) programmes (Agarwal, Taffler, Bellotti, & Nash, 2016), providing information through various communication channels. Among these channels are channels supported by information technology, such as corporate websites and social media, which have become an essential part of IR programmes. For example, firms use their websites to provide information (Ettredge, Richardson, & Scholz, 2002) and broadcast conference calls (Bushee, Matsumoto, & Miller, 2003) and social media to disseminate corporate announcements (Jung et al., 2018).

Among the social media platforms, Twitter provides an accessible communication channel that enables customers, investors and firms to engage with each other in a two-way conversation by posting tweets and receiving comments. For example, from the investor perspective, X. Li, Xie, Jiang, Zhou, and Huang (2018) have proposed a framework for monitoring emerging technologies and by using patent analysis and Twitter data mining. Such monitoring can facilitate early investments and high return on these in due course. Social media data has also been used to make stock price predictions (Daniel, Neves, & Horta, 2017) or to detect corporate fraud (Xiong, Chapple, & Yin, 2018). From the firms' perspective, unlike other communication channels, Twitter provides a unique mechanism that allows distinctions to be made about the effect of firms' dissemination decisions. Firstly, firms that seek to disseminate press releases would send investor-related information to newswire services or other information intermediaries (Bushee & Miller, 2012). It is difficult for firms to be certain about when or even whether the information would be broadcast to investors. Conversely, firms on Twitter have the option to choose the time to distribute investor information. Secondly, Twitter makes it possible for firms to know the size of their audience, which may motivate firms' dissemination decisions. Thirdly, the design of Twitter messages suggests that it is more likely to use tweets for dissemination rather than distributing comprehensive information. Tweets are limited to 140 characters, and often include hyperlinks to full press releases (Blankespoor et al., 2014) or quotes from either press releases or conference calls (Jung et al., 2018). Even though Tweets could be stand-alone pieces of information, Blankespoor et al. (2014, p. 81) "*find evidence that they are more commonly used as a method of dissemination*". Fourth, prior literature has explored various aspects of voluntary disclosure channels (Bushee et al., 2003; Ettredge et al., 2002). Twitter provides different mechanisms that support the dissemination role. For instance, conference calls are infrequent and are limited to a short period, whereas firms can use Twitter more frequently. Also, corporate websites require investors to search through the whole website for the desired information, which takes time and effort. In contrast, Twitter does not wait for investors to look for information about the firm as it applies ‘push’ technology, which directly reaches investors and reduces the acquisition cost of information. Fifth, the spread of tweets can also reach more than the firm's followers as Twitter enables the followers to redirect and share tweets with their follower lists, through the ‘retweet’ feature. Finally, firms can repeatedly post tweets over days or use hashtags (#earnings) or cashtags ($Ticker) that are ideally used to share opinion and spread news, which is expected to enhance investor recognition about a firm. All these features enable firms to expand the reach of firm disclosure on a timely basis, isolating the effect of dissemination from disclosure. Once investors receive and read this information, they can become less concerned about information asymmetry.

As this platform has become popular, researchers have paid more attention to studying the market consequences of disseminating information on Twitter. For a list of technology firms, Blankespoor et al. (2014) show that dissemination through links to press releases on Twitter reduces information asymmetry and improves market liquidity, especially for firms with a weaker information environment. In line with this, Prokofieva (2015) finds similar results for an Australian sample (100 ASK). Meanwhile, firms are most likely to use Twitter to strategically disseminate favourable news (Jung et al., 2018). Firms can also use Twitter to attenuate negative market reaction to unfavourable news such as product recall crises (Lee et al., 2015), acquisition announcements (Mazboudi & Khalil, 2017) and negative earnings surprises (Miller & Skinner, 2015). The attenuation effect suggests that firms that have better interaction, response and control to adjust investors’ concerns mitigate the reputation damage of negative corporate announcements. As a firm loses control, other users’ tweets may aggravate the adverse reaction (Lee et al., 2015). Overall, prior studies generally highlight how firms’ dissemination decisions on Twitter in spite of other information intermediaries influence the capital market in many aspects (Blankespoor et al., 2014; Jung et al., 2018). Also, using Twitter makes it possible to understand manager behaviour toward dissemination decisions. However, prior research (Botosan, 1997) has shown that managers strategically adjust disclosure decisions in a way to achieve their goals by increasing firm value and reducing the COE. We, therefore, attempt to fill such a gap in the research by studying the impact of the firm's dissemination of financial information on the COE.

2.3 *iDisc* and cost of equity (COE)

According to the "*market-liquidity hypothesis*", information asymmetry introduces adverse selection problem into transactions between market participants, and, therefore, should reduce market liquidity in firm shares (Glosten & Milgrom, 1985; Leuz & Verrecchia, 2000; Mangena et al., 2016). Firms are hence issue shares at a discount as investors pay less for shares that have high transaction costs (Amihud & Mendelson, 1986). Firms alleviate the adverse selection problem between the firm and its investors (Verrecchia, 1983) and reduce information asymmetries among informed and uninformed investors (O. Kim & Verrecchia, 1994) by voluntarily disclosing their information to decrease investors' incentives to acquire costly private information (Diamond & Verrecchia, 1991) and increase market participants' demand for the firm's stock, thus lowering the firm's cost of equity (Beyer et al., 2010; Easley & O'hara, 2004). However, information about the firm may not reach the public effectively, and greater dissemination could play a role in improving the effectiveness of disclosure. As such, Twitter allows firms to make their own dissemination decisions and be less dependent on other information intermediaries such as the press. That is, *iDisc* is likely to improve the effectiveness of firm information (in turn reducing the COE) by pushing information more directly and immediately to a broader reach of market participants, including uninformed investors. As investors receive firm information on a timely basis, they become less concerned about information asymmetry and thus improve stock liquidity and reduce the cost of equity.

Recently, Blankespoor et al., 2014; Jung et al., 2018 have argued that firms may disseminate their information on Twitter to reach many potential investors. Accordingly, the '*investor recognition hypothesi*s' suggests that improving investor recognition of the firm will increase stock prices and reduce the cost of equity (Lehavy & Sloan, 2008; Merton, 1987). The key assumption here is that investors, among all firms, only buy the stocks of firms that they recognise. Therefore, stock prices increase when more investors know about the firm. If only a small number of investors are aware of the firm's stock, then these investors will take a larger portion of the stock. For this reason, stock with lower investor recognition needs to offer a higher rate of return for the risk that investors gain from the large undiversified position. One way to enhance investor recognition is to present information to market participants through more dissemination channels. Therefore, firms can use *iDisc* to improve the breadth of their information. As information is widely disseminated, investor awareness of the firm's news increases, which improves investors' risk sharing and reduces the cost of equity. In addition, the value of dissemination rises when investors become aware of the stock, by reducing the acquisition costs that investors gain from their limited time and attention to firm disclosure (Hirshleifer, Lim, & Teoh, 2009; Hong & Stein, 1999). Such costs limit the information that investors process from corporate disclosure and make them mainly depend on a limited number of communication channels (Hirshleifer & Teoh, 2003). For this reason, firms attempt to improve the dissemination of corporate disclosure in many information intermediaries such as Twitter (Blankespoor et al., 2014). Such an improvement of dissemination is expected to provide investors with information about the firm at a lower acquisition cost, which reduces the information asymmetry and hence reduces the cost of equity.

Based on the above, we conjecture that a higher use of *iDisc* is predicted to enhance investors' reach with the firm information. This is likely to reduce the gap between informed and uninformed investors. As firms rely more on the use of *iDisc* to disseminate news, investors can receive the news at a low acquisition cost and with better investor recognition. Thereby, a higher level of *iDisc* use is expected to reduce COE.

H_1: There is a significant negative association between *iDisc* and the cost of equity (COE).

While we argue that disseminating financial information (*iDisc*) on Twitter improves a firm's information environment to reduce the cost of equity by enhancing firm connection and information availability and accessibility to investors, the firm's information environment is also affected by other factors such firm size, book-to-market ratio (*BTM*) and financial leverage (*LEV*). Larger sized firms have a better information environment (Gebhardt et al., 2001) and expect to have lower costs of equity (Botosan, 1997; Dhaliwal, Heitzman, & Zhen Li, 2006; Mangena et al., 2016, whereas smaller firms have a lower information environment, lower liquidity and hence expect to have a higher COE. Therefore, firm size (*SIZE*) is expect to have a negative association with COE.

H_2: There is a significant negative association between firm size (*SIZE*) and the cost of equity (COE).

In addition, the book to market ratio (*BTM*) reflects the difference in firm accounting conservatism and investment opportunities (Hail & Leuz, 2006). This variable is considered a risk factor (Easton, 2004; Mangena et al., 2016). That is, firms with a higher *BTM* ratio are undervalued in price and should have a higher risk premium (Fama & French, 1992; Gode & Mohanram, 2003). In this sense, we expect the book-to-market ratio (*BTM*) to be positively associated with COE.

H_3: There is a significant positive association between firm book-to-market (*BTM*) and the cost of equity (COE).

According to Modigliani and Miller (1958), firms that use more financial leverage face greater financial uncertainty and expect to have higher risk premiums. Firms with a high leverage ratio may face more liquidity risk that arise from limiting their ability to meet their obligations. Furthermore, those firms may also encounter more restrictions in their ability to access external funds, which in turn might affect the analyst evaluation from the credit rating perspective. Therefore, firms with higher debt on their capital structure may have a higher cost of equity (Cao et al. 2015; Dhaliwal et al, 2006; Fama & French, 1992). We, therefore, expect a positive association between *LEV* and COE.

H_4: There is a significant positive association between firm financial leverage (*LEV*) and the cost of equity (COE).

The uncertainty surrounding the information environment due to wider dispersion of analysts' forecasts is expected to increase firm risk (Gode & Mohanram, 2003; Kothari et al., 2009a). That is, wider dispersion or disagreement in analysts' forecasts implies greater uncertainty about earnings forecasts (El Ghoul, Guedhami, Kim, & Park, 2018; Guedhami & Mishra, 2009), implying a greater risk for the firm information environment and hence a higher cost of equity. Therefore, we expect a positive relationship between dispersion analyst (*DISP*) and cost of equity (COE).

H_5: There is a significant positive association between firm analysts' forecast dispersion (*DISP*) and the cost of equity (COE).

Under the capital asset market pricing model, investors expect a higher required rate of return as systematic risks become higher. Systematic risk or market beta (*BETA*) is an undiversifiable risk that increases the firm risk premium (Botosan, 1997; Botosan, Plumlee, & Wen, 2011; Cao et al., 2015; El Ghoul et al., 2011). As the risk increases, the certainty that investors expect to earn from their investment will become smaller, which, in-turn, increases their required return on their investment. Consequently, firms with high systematic risk (*BETA*) are expected to have a higher COE.

H_6: There is a significant positive association between firm systematic risk (*BETA*) and the cost of equity (COE).

Prior literature (Cao et al., 2015; Guedhami & Mishra, 2009) indicates that firms with a high long-term growth rate (*LTG*) are considered riskier and have more uncertainty than lower LTG firms. Thai is, high prospect about firm growth and earnings may result in the inflation of stock prices and that any misestimating of growth rate can have a significant effect on the share price (Chen, Chen, & Wei, 2011; Gode & Mohanram, 2003). Therefore, the market perceives a firm with high LTG as a high-risk investment and hence they expect a higher cost of equity. Therefore, we predict a positive association between *LTG* and COE.

H_7: There is a significant positive association between the long term growth forecast (*LTG*) and the cost of equity (COE).

While media coverage may shape the firm information environment, which is expected to influence the expected rate of return, the press may contain additional information and favour a direction of news stories that could influence the firm valuation and cost of equity (Fang & Peress, 2009; Jung et al., 2014; Niessner & So, 2017). Kothari et al. (2009a) find that media coverage increases the firm's cost of equity when the news is negative, whereas positive news reduces the equity financing. Therefore, we do not provide any certain direction between media coverage (*NEWS*) and COE.

H_8: There is no significant association between media coverage (*NEWS*) and the cost of equity (COE).

The existence of institutional investors enhances the monitoring role on firm management, exerting more pressure on them to provide better information quality, transparency and management practices (Attig, Cleary, El Ghoul, & Guedhami, 2012; Elyasiani & Jia, 2010). This enhancement of the monitoring and information role reduces the agency problem and information asymmetry between market participants and hence reduces the cost of equity (see Attig, Cleary, El Ghoul, & Guedhami, 2013; Elyasiani, Jia, & Mao, 2010). Therefore, we expect that high institutional holdings are likely to enrich the firm public information environment, reducing the uncertainty and thus reducing the cost of equity.

H_9: There is a significant negative association between firm institutional holdings (*INSTOWN*) and the cost of equity (COE).

Firm managers may have an incentive not to miss earnings expectations. Previous studies (Mikhail, Walther, & Willis, 2004) have argued that earnings surprise can be costly to the firm as analysts would not prefer to follow firms with an earnings surprise. That is, an earnings surprise may cause an analyst's forecast to be inaccurate, which is not preferable for many analysts, resulting in lower analyst coverage and thus a lower information environment. In other words, an earnings surprise reflects the uncertainty surrounding the current earnings, which imposes a higher risk and is expected to increase the cost of equity (El Ghoul et al., 2011; Kim & Shi, 2011; Rogers, Skinner, & Van Buskirk, 2009). Therefore, we expect earning surprise (*SURP*) to be possibly associated with the cost of equity (COE).

H_{10}: There is a significant positive association between earnings surprise (*SURP*) and the cost of equity (COE).

Finally, firms with better performance, stable profitability and increase in earnings are expected to have lower uncertainty and less exposure to default risk (e.g. El Ghoul et al., 2018; Francis, Khurana, & Pereira, 2005; Gode & Mohanram, 2003). Previous studies (Bowman, 1979; Francis et al., 2005) indicate that default risk is positively associated with equity risk, which is a result of an increase in the cost of equity. Thus, we expect a negative association between return on assets (ROA) as a measure of firm profitability and COE.

H_{11}: There is a significant negative association between return on assets (*ROA*) and the cost of equity (COE).

In figure 1, we show the effect of our explanatory variables on COE.

[Insert Figure 1 about here]

3. Methodology

3.1 Sample and data

Our initial sample includes non-financial firms listed on the US NASDAQ stock exchange that have official Twitter accounts. Our sample focuses on the US because foreign firms have different information environments, and the dissimilarities in transparency can influence the COE. The SEC, the regulator of the US stock markets, allows firms to use social media such as Twitter for disclosing financial information that complies with Regulation Fair Disclosure (Dorminey, Dull, & Schaupp, 2015). US firms have shown frequent adoption of Twitter and early use for corporate announcements (Jung et al., 2018; Zhou, Lei, Wang, Fan, & Wang, 2014), which ensured a potential coverage during our sample period. Consistent with Bushee et al. (2010), we mainly focus our sample on one stock exchange to remove any effect of exchange listing.

We focus on 2009-2015, even though Twitter was founded in March 2006, because Twitter accounts' popularity grew among its users around 2009 (Marwick & Boyd, 2011). We also exclude tweets before 2009 to avoid the macroeconomic effects of the financial crisis (2007-2008), limited Twitter activity (approximately less than 10% of our sample had Twitter accounts before 2009), and limited use of cashtags in Twitter before 2009.

Our data collection strategy is based on identifying whether each firm in the sample has a Twitter account, using a number of checks (e.g. whether they had the Blue Verified Twitter Badge). After identifying Twitter adopter firms, we check whether these firms have positive median earnings forecasts for one and two years ahead to measure the implied COE. These consensus earnings forecasts are collected as of June to ensure that analysts had incorporated all the information from fiscal year reports in their forecasts. Firms with missing observations on the COE are excluded from the sample. These restrictions reduce the sample size to 791 firms (4,131 firm-year observations).

Corporate adoption of Twitter does not necessarily mean using their Twitter accounts for disseminating financial information (*iDisc*). We, therefore, use two sources to download the full texts of tweets to identify *iDisc*. We retrieve Twitter data from both Twitter's application programming interface (API) and Twitter's advanced search. Twitter API provides a maximum number of tweets (up to 3,200 tweets). Tweets beyond 3,200 are, therefore, manually collected through Twitter's advanced search function. Manual collection is performed to obtain tweets between the last collected tweets from Twitter API and the first tweet published by the firm's account. If the number of tweets is large, we use the advanced search option to search for financial keywords. We used keywords that related to financial capital, balance sheet items, equity and debt financing, financial ratio and financial reporting and announcement (discussed further in Measuring *iDisc*). The total number of tweets collected is 1,197,208 tweets, approximately 2/3 of which come from Twitter API. The mean (median) value of the number of tweets is 4,588 (944), which suggests that the total number of collected tweets is not particularly large. We process these tweets through a matching classification scheme to quantify *iDisc* tweets.[1]

[1] The classification process followed several steps: (1) we uploaded the data to the Python software programme; (2) we read all these data; (3) we applied "stop words", which is a process used to remove words that have no meaning in the text (e.g. "a", "the", "and"); (4) we divided tweets into words by applying a technique to split the text into separate words; (5) we matched the word in each tweet with our financial keyword list ; (6) we gave a value of 1 to every tweet that matched with our list of keywords; (7) we downloaded the data into an Excel file for tweets that matched our classifications.

In addition to Twitter data, we collected all news articles that mentioned the firm's name from LexisNexis. This database includes major news media channels such as *Wall Street Journal*, *The New York Times*, *The Washington Post* and *USA Today*. We used company identifiers to allocate all firm news in the database. We define news coverage as the total number of news articles about the firm. In addition, we obtained accounting and market data to measure the dependent and explanatory variables from Bloomberg and DataStream. The distribution of the sample shows high skewness from the medians for *COE, LEV*, *DISP*, *BETA*, *LTG* and *ROA.* These high skewnesses suggest the existence of outliers, which may mislead the interpretation of the estimated coefficient. To control for the outliers, we winsorize all these variables at the 2.5^{th} to 97.5^{th} percentiles. Consistently with previous literature (Botosan et al., 2011; Chen et al., 2009), we winsorize the COE to lie between 0 and 0.6 as investors are not expected to require negative rates of return and high COE could be driven by outliers.

3.2 Measuring iDisc

We focus on financially related information (iDisc-related tweets), as financial information is important to investors and firms are mandated to disclose this information but are not required to disseminate it on Twitter. This makes it possible to distinguish the effect of dissemination from disclosure (Jung et al., 2018). To identify *iDisc* tweets from *big data* of firm tweets, we search for the existence of financial information by combining several sets of financial keywords or using single phrases. For instance, we use the following keywords and phrases to look for earnings-related tweets:

("earning", "revenue*", "profit*", "income", "loss*", "sales", "dividend", "financial") AND ("disclos*", "report*", "record*", "perform*", "statement*" "release*", "announce", "quarter", "annual", "result*")

We also use other financial keywords that relate to financial reporting, stock prices, balance sheet items and their variants such as:

("annual report*", "annual statement*", "press release*", "balance sheet", "cash flow", "cash inflow", "total assets", "current assets", "total liabilit*", "current liabilit*", "long term assets", "long term debt", "net income*", "net profit*", "capital gain", "net loss*", "capital loss", “capital expenditure*”, “market capital*”, “stock pric*”, “secur* pric*”, “share* pric*”, “merger”, “acquisition”, “earnings per share”, “stock* repurchase”, “share* repurchase”, “stock* offering”, “share* offering”)

The development of financial keyword lists starts with identifying words used in previous studies (Campbell, Chen, Dhaliwal, Lu, & Steele, 2014; Kothari et al., 2009a; Kravet & Muslu, 2013; Matsumoto, Pronk, & Roelofsen, 2011). The strategy of developing word lists includes searching and adding other synonyms for financial words through WordNet and other dictionary software applications. Additional terms and synonyms have been added from Campbell Harvey’s financial glossary lists (Harvey, 1999). Terms or words that relate to firm activity, reporting, announcements and disclosure were included in the lists. To reduce the classification error, we look for the existence of multiple words in the same tweet.

In addition, Twitter provides features that firms can use to push information regarding any event or topic by using the hash key (#). These hashtags can be used for earnings announcements or quarter earnings events. Twitter also makes it possible for users and firms to discuss and disseminate a firm’s financial information through the cashtag key feature ($ticker). Thus, we also included hashtags that are used for firm announcements and cashtags in our keywords list, such as:

(“#earnings”, “#quarterearnings”, “#annualreport*”, “#pressrelease”, #Q12014, e.g. $AAPL for Apple inc).

Tweets that match with our list of keywords are quantified as *iDisc* tweets. Our analysis examines the annual number of *iDisc* tweets for each firm in our sample period.

3.3 The empirical model

To examine the impact of *iDisc* and other explanatory variables on the implied cost of equity premium we employ the following Model (1):

$$\begin{aligned} \mathrm{COE}_{it} = {} & \beta_0 + \beta_1 \mathrm{iDisc}_{it} + \beta_2\,\mathrm{SIZE}_{it} + \beta_3\,\mathrm{BTM}_{it} + \beta_4\,\mathrm{LEV} + \beta_5\,\mathrm{DISP}_{it} + \\ & \beta_6\,\mathrm{BETA}_{it} + \beta_7\,\mathrm{LTG}_{it} + \beta_8\,\mathrm{NEWS}_{it} + \beta_9\,\mathrm{INSTOWN}_{it} + \\ & \beta_{10}\,\mathrm{SURP}_{it} + \beta_{11}\,\mathrm{ROA}_{it} + \beta_{12} \textstyle\sum_{t=2015}^{2009} \mathrm{T}_t + \beta_{13}\,\mathrm{v}_i + \varepsilon_{it} \end{aligned} \tag{1}$$

The dependent variable in this model (*COE*) is the implied COE, which is estimated as the average of four equity premium estimates: (i) Claus and Thomas model, R_{CT} (2001); (ii) Gebhardt, Lee, and Swaminathan model, R_{GLS} (2001); (iii) Ohlson and Juettner-Nauroth model, R_{OJ} (2005); and (iv) Easton model, R_{MPEG} (2004). The use of an average of these measures was aimed at reducing the estimation errors (Dhaliwal et al., 2006; Dhaliwal, Judd, Serfling, & Shaikh, 2016; Hail & Leuz, 2006). The implied COE is a good measure for the COE, because it attempts to differentiate the effect of growth and cash flow from the COE (Chen, Chen, & Wei, 2009). Pástor, Sinha, and Swaminathan (2008) also indicate that the implied COE is a useful estimate for the time-series variation of expected returns.

iDisc reflects the number of financial tweets. This measure is computed by employing the words, phrases and combined word classification. We cluster tweets based on the existence of specified words or phrases. We only count tweets that matched the criteria for measuring *iDisc* or set this to zero otherwise. Our variables also include firm size (*SIZE*), book-to-market ratio (*BTM*), financial leverage (*LEV*), the dispersion of analysts forecast (*DISP*), systematic risk (*BETA*), long-term growth rate (*LTG*), press coverage (*NEWS*), institutional holdings (*INSTOWN*), earnings surprise (*SURP*) and return on assets (*ROA*). In addition to iDisc, these variables are related to firm characteristics, analysts' forecast attribute, systematic risk, information intermediaries, content of information and firm profitability. In Table 1, we list all our independent variables and their direction with COE. Additionally, full descriptions of the variables and measurements are presented in Appendix A. Appendix B provides all the model measurements and descriptions for measuring COE. In addition, we include both year and industry fixed effects in the regressions using the Fama-French 12-industry classification.

[Insert Table 1 about here]

Our estimation procedures utilised pooled cross-sectional regressions with robust standard error clustered at the firm level to control for serial correlation and heteroscedasticity (Cao et al., 2015; El Ghoul, Guedhami, Kim, & Park, 2018; Petersen, 2009).[2] To mitigate potential endogeneity between *iDisc* and the COE (Nikolaev & Van Lent, 2005), we utilise a two-stage

[2] The Breusch-Pagan test shows significant results (*p*-value = 0.000; 0.031; 0.000 respectively), indicating the presence of heteroscedasticity.

least square model (2SLS) with clustered standard error at the firm level.[3] We use *non-iDisc tweets in the previous year* (*LagPriortweet*) as the instrumental variable in line with prior social media and business press literature (Drake et al., 2014; Lee et al., 2015). This instrumental variable is related to *iDisc* and is not directly related to the COE. In addition, *LagPriortweet* captured the prior tendency of firm activity and responsiveness in their Twitter account, which is likely to be correlated to *iDisc*. This measure also represents the amount that corporate firms added to their Twitter accounts. The results of the partial square are higher than 0.22, and the *F* statistic was greater than the critical value of 10 (Staiger & Stock, 1994). Also, the association between *LagPriortweet* and *iDisc* is positive and significant, which is consistent with our prediction and the previous literature (Lee et al., 2015).

4. Results and discussion

4.1 Descriptive statistics

Table (2)-Panel (A) reports the percentage of firms that have adopted Twitter and use *iDisc* in our sample. Results show that over 66% of firms used *iDisc* at least once in our sample period and 44% of the firms have disseminated financial information over Twitter at least for three years. This finding is comparable with Jung et al. (2018), who found that more than 57% of firms that have a Twitter account disclose earnings-related tweets. Panel (B) shows that the percentage use of each *iDisc* class varies across the years and the average number of tweets per year. We find that the mean number of *iDisc* tweets of the full sample is, on average, seven tweets per year per firm. Results show that the number of such tweets grows substantially over time, which offers some primary highlights about the role of Twitter in the dissemination of financial information by firms. This can be justified through the SEC guidance, in April 2013, which motivates firms to use Twitter for dissemination purposes (Dorminey et al., 2015). In addition, results show that financial reporting tweets are the dominant type of *iDisc*, two-thirds of *iDisc* being related to financial reporting, which far exceeded other types. This finding is consistent with Jung et al. (2018), who found a higher number of tweets related to the earnings releases. Our results also show that 7%, 21%, and 15% of *iDisc* tweets were related to financing, financial terms, and financial ratio respectively.

[3] To test for the endogeneity, we ran the Durbin Wu-Hausman test. The results show an *F* test (*P*-value) of 1.54 (0.215), suggesting that endogeneity is prevalent.

[Insert Table 2 about here]

Table 3 provides summary statistics of *iDisc* activity based on the Fama-French 12-industry classification. The distribution of *iDisc* tends to be heterogeneous across industries. The highest use during the whole sample period is prevalent in the business equipment industry. For this industry, at least half of the companies used *iDisc* once, which represents approximately 37% of the total number of firms that use *iDisc*. This result is expected given that firms in the business equipment industry are more likely to adopt this new communication channel (Blankespoor et al., 2014). Although the oil and gas industry shows a high reliance on *iDisc*, consistent with Jung et al. (2018), the percentage of *iDisc* tweets is rather low as compared to other sectors, with a low concentration for the number of firms. In contrast, firms in food, tobacco, textiles, apparel, leather and toys classifications tend to focus more on non-financial information.

[Insert Table 3 about here]

Table 4 provides descriptive statistics for the variables considered. The summary statistics of the dependent variables show that the mean estimate of *COE* is 5.1%, which is in line with the prior evidence (Attig et al., 2013; Chen et al., 2011; El Ghoul et al., 2011). *COE* is based on four estimates: R_{OJ}, R_{MPEG}, R_{CT} and R_{GLS}. In comparison, R_{OJ}, R_{CT} and R_{GLS} show higher premiums than *COE* of 6.7%, 5.8% and 10.2% respectively, whereas a lower premium of 4.4% is associated with R_{MPEG}. The mean of firm size (*SIZE*) is 20.25, and the unreported mean (median) of firm size is $4106.6 million ($562.8 million). The mean (median) of book-to-market (*BTM*) equals -1.374 (-1.029). Sample firms have a mean financial leverage (*LEV*) of 16%. The median of dispersion (*DISP*), systemic risk (*BETA*) and the long consensus forecast of earnings estimates (*LTG*) are 9.3%, 1.15% and 15% respectively. Also, the mean and median of *BETA* are greater than one, which indicates that the sample consists of firms that have higher systematic risk than the market. These results are comparable to prior studies (Cao et al., 2015). Additionally, the average news coverage (*NEWS*) is 5.557, and approximately 77% of firms are owned by institutional owners (*INSTOWN*). The mean average of earnings surprise (*SURP*) is equal to 0.365, which is in line with (Chen et al., 2011). However, the mean of the profitability measure (*ROA*) is negative (7%), compared to a positive median of 2.2%.

[Insert Table 4 about here]

The Spearman and Pearson correlation matrix is presented in Table 5 for all the variables at the 10% significance level. The correlation matrix shows a significant and negative correlation between *COE* and *iDisc*. This finding provides a preliminary conclusion that firms which use *iDisc* have a lower COE. Results indicate that smaller (larger) sized firms have a higher (lower) COE. High risk, measured by *BTM*, *LEV*, *DISP*, *BETA*, *LTG* and *SURP*, is associated with high risk-premiums. Richer information environment variables (*NEWS* and *INSTOWN*) are negatively correlated with *COE*. Overall, correlations between *COE* and the other independent variables are in line with expectations and previous studies (Orens et al. 2010; Cao et al. 2015; Dhaliwal et al. 2016). Moreover, in Table 5 *iDisc* is negatively correlated with *BTM*, *LEV*, *BETA*, *LTG*, *INSTOWN* and *ROA*, but is positively correlated with *SIZE*, *DISP*, *NEWS* and *SURP*. These correlations suggest that enhanced *iDisc* alleviates the uncertainty and risk factors. The positive correlation between firm *SIZE* and *iDisc* indicates that larger firms publish more *iDisc* tweets. Furthermore, firms with a higher rate of news (*NEWS*) use *iDisc* more. These correlations, together, suggest that firms with lower uncertainty are more likely to release financial information on Twitter. In addition, the results show that lower return on asset (*ROA*) firms use *iDisc* more frequently. Considering both the Spearman and Pearson correlation matrix and unreported VIF tests indicates that multicollinearity is not dominant across our explanatory variables.

[Insert Table 5 about here]

4.2 Empirical results

Table 6 reports the results of the two estimation models (i.e., OLS in column 1 and 2SLS in column 2) for the association between *iDisc* and *COE*. Results show a negative and statistically significant association between *iDisc* and *COE* ($p < 0.05$) in OLS and ($p < 0.1$) in 2SLS.[4] Our results show that the economic significance of *iDisc* is -0.14%, which means that if *iDisc*

[4] The reduction in sample size is due to the additional data requirements. To check whether our results are affected by missing data, we also ran the regression with the lagged *iDisc* as the instrumental variable. The Lagged *iDisc* can be an appropriate instrument as it is less likely to affect the cost of equity once year later. The Hausman test is 0.79, with first stage partial square equal to 0.52. Our main results remain unchanged.

tweeting increases by 50%, the COE is expected to change by -0.07%. However, the finding suggests that firms that disseminate more financial information (*iDisc*) have a lower COE. This implies that firms' decisions to engage in broader dissemination actions through *iDisc* promote financial benefits for both investors and managers. That is, investors can receive a firm's information at a lower acquisition cost and managers are able to alleviate the information asymmetry as well as enhance investor recognition. Although tweets are not expected to have comprehensive information, the results show that *iDisc* can still reduce *COE,* which supports our hypothesis. This finding is in line with our expectation that the effect of tweets should be small as it is less likely to have rich information. However, tweets provide an accessible (open) use for managers at lower costs, efficient timings and better control. This finding is consistent with other communication mechanisms such as corporate websites and open conference calls that firms can use to disseminate their information to the public openly (Orens et al., 2010; Zhao, Davis, & Berry, 2009). Nevertheless, these channels are used as primary channels for disclosing corporate information whereas Twitter is used for dissemination of information.

[Insert Table 6 about here]

With respect to other variables, across the two columns, we find a negative coefficient on firm size (*SIZE*) and positive coefficients on the book-to-market ratio (*BTM*) and financial leverage (*LEV*), which is consistent with hypotheses H_2, H_3 and H_4. Additionally, *COE* tends to significantly increase systematic risk (*BETA*), with positive coefficients, which is consistent with our prediction in H_6. These findings suggest that firms with higher uncertainty are associated with a higher required rate of return. The coefficient on *LTG* is positive and significant, which supports hypothesis H_7, indicating that the market perceives high growth firms as riskier. News coverage (*NEWS*) shows a positive association, which suggests that more news coverage, which is not under the firm's control, increases the COE, rejecting the null hypothesis H_8. That is, firms with higher media coverage face more risk than lower coverage firms. These firms have higher stakeholder pressure as they are exposed to more stakeholder groups (Zyglidopoulos, Georgiadis, Carroll, & Siegel, 2012). They also have higher levels of scrutiny from stakeholders, which makes them more vulnerable to campaign targets (Friedman, 1991; Rehbein, Waddock, & Graves, 2004). In addition, previous literature (Niessner & So, 2017) found that media coverage may favour negative news. Therefore, firms with more news coverage could face higher risks of getting into difficulties when the media provide misshaping or negative news, which consequently increases the COE capital (Kothari et al., 2009a). The coefficient on earnings surprise (*SURP*) in column (2) is significantly positive, suggesting that firms that have higher optimism about analysts' earnings forecasts have a greater COE (El Ghoul et al., 2011), which confirms hypothesis H_{10}. However, our results show no association for *DISP*, *INSTOWN* and *ROA*.

4.3 The firm visibility effect

Firms seek to attract investor attention, as well as reduce investor acquisition costs, by disseminating information through many information intermediaries (Hirshleifer et al., 2009; Hirshleifer & Teoh, 2003). If firms with low press coverage rely on a small number of communication channels which are reasonably affordable, there is a high chance that investors will not receive news about the firm on a real-time basis. Therefore, low (high) visible firms are less (more) likely be frequently observed by market participants, and, hence, lower (higher) investor recognition and higher (lower) COE are likely (Merton, 1987). Accordingly, low visibility firms might have a higher need to disseminate firm news and, hence, rely more on *iDisc*. Under these scenarios, *iDisc* will help firms improve firm visibility and be less dependent on other information intermediaries, by voluntarily making dissemination decisions and directly approaching market participants promptly (Blankespoor et al., 2014; Jung et al., 2018). As such, we predict that the impact of *iDisc* on the implied COE is more pronounced for less visible as compared to more visible firms.

To measure firm visibility, we have used firm size (*SIZE*), analyst following (*ANALYSTS*) and the number of investors (*LNOWN*) as proxies for a firm's visibility, where the upper quartile (lower three quartiles) is used to proxy for highly visible (low visible) firms. These proxies are in line with Merton (1987), who argues that there is a stronger effect of investor recognition for firms with higher idiosyncratic risk. That is to say, firms with a smaller size, low analyst following, and a limited number of investors are less visible to market participants (Agarwal et al., 2016). Although firms may issue voluntary disclosure to attract market participants, smaller sized firms are likely to be neglected and may not be able to benefit from such actions (Bushee & Miller, 2012). To overcome this concern, some firms attempt to initiate investor relation programmes to attract investor recognition and analyst followings (Bushee & Miller, 2012). This is likely to provide valuable communication sources to mid-size and/or small firms, given that large a analyst following is associated with an increased demand for the firm's stock, which as a result improves the firm's value (Agarwal et al., 2016). Also, previous research

(Lehavy & Sloan, 2008) has argued that firm value is positively associated with the investor base.

We partitioned the full sample into high and low visibility firms under each variable, and the results are presented in Table 7 using OLS and 2SLS estimations with clustered standard errors at the firm level. The findings provide strong evidence that lower-visibility firms use *iDisc* to reduce their COE, with significant and negative coefficients reported under columns 3, 4, 6 and 8 ($p < 0.05$, $p < 0.1$, $p < 0.01$ and $p < 0.1$ respectively). These findings are also consistent with prior studies which show that the effect of investor recognition is more pronounced for small-sized firms (Agarwal et al., 2016; Blankespoor et al., 2014; Merton, 1987). Additional evidence suggests that corporate disclosure reduces the COE for firms with low information certainty, low analyst following and a limited number of investors (Botosan, 1997; Orens et al., 2010). In contrast, we find that high-visibility firms with high investor awareness tend not to rely on *iDisc* to reduce the COE and consistently show insignificant associations with *COE*. This might be attributable to large firms having more analysts following them and a larger number of shareholders. Accordingly, these firms seem to benefit from other channels of dissemination and may be reached by more traditional information intermediaries. Overall, these findings are consistent with the notion that broader dissemination to the public on Twitter improves firm visibility, which leads to better recognition and lower cost of equity, consistent with prior literature (Agarwal et al., 2016; Blankespoor et al., 2014; Cao et al. 2015; Lehavy & Sloan, 2008).

[Insert Table 7 about here]

4.4 The effect of news magnitude and content

Firms are likely to have incentives to disclose good news rather than bad news to positively affect their stock value (Skinner, 1994). Therefore, firms are expected to increase their dissemination of good news on Twitter, rather than negative news. Nevertheless, firms could also use Twitter to attenuate the effect of unfavourable firm announcements such as negative earnings surprise (Miller & Skinner, 2015) or product recall (Lee et al., 2015). As such, we conjecture that firms that miss analysts' forecasts have less incentive to use *iDisc* as compared to those with a positive earnings surplus. We expect that voluntary disclosure could be used to match managers' and market expectations (Matsumoto, 2002).

To examine the effect of news magnitude (i.e. negative/positive earnings surprises) on the conditional use of *iDisc* to reduce the COE we utilize our base Model (1) to additionally control for the absolute earnings surprise (|*SURP*|) as an indicator variable for negative earnings surprise (*NegSURP*), which takes the value of one when *SURP* is negative and zero otherwise. We also include two interaction variables between absolute earnings surprise with *iDisc* (|SURP| * *iDisc*) and negative earnings surprise (|SURP| * *NegSURP*). Therefore, we specify Model (2) as follows:

$$\begin{aligned}\mathrm{COE_{it}} = {} & \beta_0 + \beta_1 \mathrm{iDisc_{it}} + \beta_2\, |\mathrm{SURP}|_{\mathrm{it}} + \beta_3\, \mathrm{NegSURP_{it}} + \beta_4\, |\mathrm{SURP}|_{\mathrm{it}} * \\ & \mathrm{iDisc_{it}} + \beta_5\, |\mathrm{SURP}|_{\mathrm{it}} * \mathrm{NegSURP_{it}} + \beta_6\, \mathrm{SIZE_{it}} + \beta_7\, \mathrm{BTM_{it}} + \\ & \beta_8\, \mathrm{LEV} + \beta_9\, \mathrm{DISP_{it}} + \beta_{10}\, \mathrm{BETA_{it}} + \beta_{11}\, \mathrm{LTG_{it}} + \beta_{12}\, \mathrm{NEWS_{it}} + \\ & \beta_{13}\, \mathrm{INSTOWN_{it}} + \beta_{14}\, \mathrm{ROA_{it}} + \beta_{15} \textstyle\sum_{t=2015}^{2009} \mathrm{T_t} + \beta_{16}\, \mathrm{v_i} + \varepsilon_{\mathrm{it}}\end{aligned} \tag{2}$$

Since firms have the option to use Twitter, firms may use *iDisc* to provide more positive than negative news (Jung et al. 2017). Therefore, we extend our analysis to identify the effect of news content on the conditional use of *iDisc* to reduce the COE. Previous literature (Kothari et al., 2009a) has studied the effect of the disclosure's content by different information sources on the COE. They found different impacts on COE depending on the source (management, analysts and business press) and the content of the disclosure (favourable and unfavourable news). Johnstone (2016) also argues that the effect of financial reporting on the COE is subject to the direction of the report (what the report says). That is, bad information increases the uncertainty of future expected payoff and hence increases the COE. However, good news provides higher certainty of future cash flow and, thus, reduces the COE. To examine our predictions, using our base Model (1), we additionally include TONE as a proxy for *iDisc* contents and its interaction with *iDisc* (*TONE_ iDisc*). This measure aims to reflect whether *iDisc* tweets provide positive and negative meaning. We used Loughran and McDonald dictionary lists (2011) to identify the positive and negative words of iDisc tweets. We measured the TONE as the difference between positive and negative words divided by the sum of positive and negative words. Accordingly, our model (3) is specified as:

$$
\begin{aligned}
COE_{it} = {} & \beta_0 + \beta_1 iDisc_{it} + \beta_2\, TONE_{it} + \beta_3\, TONE_{it} * iDisc_{it} + \beta_4\, SIZE_{it} + \\
& \beta_5\, BTM_{it} + \beta_6\, LEV + \beta_7\, DISP_{it} + \beta_8\, BETA_{it} + \beta_9\, LTG_{it} + \\
& \beta_{10}\, NEWS_{it} + \beta_{11}\, INSTOWN_{it} + \beta_{12}\, SURP_{it} + \beta_{13}\, ROA_{it} + \\
& \beta_{14} \textstyle\sum_{t=2015}^{2009} T_t + \beta_{15}\, v_i + \varepsilon_{it} \qquad (3)
\end{aligned}
$$

We estimated Models (2) and (3) using OLS and the results are reported in Table 8. The result from Model (2) shows that the dissemination of financial information on Twitter (*iDisc*) is significantly associated with a lower COE even after controlling for the magnitude of the news. The results show that the coefficient of *iDisc* is equal to negative 0.13%, which indicates that increasing *iDisc* tweets by 100% (in our average the sample number of tweets across firms and years studied was 7) reduces the COE by 0.13%. Although this may be a relatively small increase in % terms, this was a result of a very small number of posted messages. Increasing them can result in a high return of the time and effort put into systematically engaging investors. The coefficients of |SURP|, NegSURP, |SURP| * iDisc and |SURP| * NegSURP are not statistically significant. These results are consistent with Jung et al. (2018), who found an insignificant result by using the total number of the firm's followers, and with the idea that the dissemination of firm initiated information may improve the information environment. The findings highlight the important role of *iDisc*, which extends beyond the type of news. Concerning the effect of news content, results for Model (3) provide evidence that the TONE of the news does not drive the negative association between *COE* and *iDisc*. Both the level and interaction variables for TONE show insignificant associations with *COE*. That is, firms' managers may benefit from *iDisc* even with unfavourable news. The overall findings provide limited support for the influence of news magnitude and news content on information dissemination through *iDisc*. These findings support our main findings and are in line with predictions.

[Insert Table 8 about here]

4.5 The effect of providing additional information and the reach of *iDisc*

In this section, we examine the association between *iDisc* on COE by considering different measures of *iDisc* and COE. First, we count the *iDisc* tweets that include hyperlinks, as this allows users to acquire more information from websites by following the posted link

(Blankespoor et al., 2014). Finally, we employ an alternative COE measure, R_{PEG} (Easton, 2004), based on long-term horizon estimates. Across different measures of COE, Botosan et al. (2011) find that R_{PEG}, which assumes no dividend payment, is a valid proxy for COE. They state that R_{PEG} is a reliable measure "associated with firm-specific risk characteristics in a theoretically predictable and stable manner" (p. 1085). Empirical studies on the relationship between corporate disclosure and the COE also use R_{PEG} as a proxy for COE (J. W. Kim & Shi, 2011; Mangena et al., 2016). The findings are presented in Table 9 and show that iDisc_Hyperlink is negatively and significantly associated with COE. This implies that tweets which permit more access to information or are diffused to extend to potential investors considerably reduce the COE. The results in column (2) show a significant and negative association between R_{PEG} (as an alternative measure of COE), which is consistent with our main findings.

[Insert Table 9 about here]

4.6 Controlling for information quality and other firm characteristics

In Table 10, we further check the robustness of our main results by controlling for a set of other variables in Model (1). First, we use discretionary accruals, based on Jones's model (Demirkan, Radhakrishnan, & Urcan, 2012; Francis et al., 2008), as a proxy for information quality. Previous literature (Hughes et al., 2007; Lambert et al., 2011) has argued that information quality has both direct and indirect (through information asymmetry) effects on the COE. Francis et al. (2008) find that the impact of financial information on the COE becomes insignificant after controlling for information precision. Theoretical models (Lambert et al., 2007) indicate that information asymmetry does not affect the COE after controlling for information quality. In column (1), we, therefore, incorporate discretionary accruals. Second, following previous research (Jung et al., 2018; Lee et al., 2015), we include an indication of the social media adoption of financial reporting, namely advertising intensity (ADVERTISING). This is calculated as total advertising expense divided by the total sales. Even though firms with high advertising expenses are more likely to have a Twitter account, firms that spend less on advertising tend to use Twitter for announcement purposes (Jung et al., 2018). We also control for whether a firm headquarters is located in Silicon Valley (SILICON) and whether the firm's manager is younger than the median age (CEOAGE). Firms that are located in Silicon Valley and have younger managers are more likely to adopt social media platforms (Lee et al., 2015). Finally, the implied COE is measured by using earnings estimates of analysts' forecasts as a prediction of market expectations. Using these estimates might be subject to criticism as the poor market expectation by analysts may bias the implied COE estimates. Accordingly, previous studies suggest controlling for analysts' sluggishness forecasts by including price momentum (Chen et al., 2011; El Ghoul et al., 2011). We, therefore, include the price momentum (MMT), measured as the compounded rate of return of the previous 6 and 12 months.

[Insert Table 10 about here]

The results in column (1) suggest that the negative effects of *iDisc* on *COE* is not affected by information quality, whereas discretionary accruals (ACCRUAL) are insignificant. This finding supports the incremental role of dissemination for corporate disclosure (Blankespoor et al., 2014; Fang & Peress, 2009), rather than the quality of information. When controlling for the effect of social media indicators, in column (2) we find a negatively significant association between *iDisc* and *COE,* while the three indicators of social media *ADVERTISING*, *SILICON* and *CEOAGE* report insignificant associations with *COE*.[5] These results alleviate any concern regarding the willingness to adopt social media and the implications of the use of *iDisc*. Finally, the results in columns (3&4) show that the two indicators of momentum are negatively and significantly associated with *COE*, which is consistent with prior research (Chen et al., 2009). These findings suggest that the noise of analysts' forecasts does not drive our results. The negative and significant association between *iDisc* and *COE* is robust, which suggests that our main findings are not affected by analysts' noise.

5. Conclusion

The amount of real-time data, "*big data*", on social media has attracted various practices among many firms due to its application and involvement in people's daily life, resulting in a great deal of attention and business change (e.g. Raguseo, 2018). Social media such as Twitter has become a popular channel for many firms to disseminate financial information by directly

[5] The decrease in the number of observations is due to missing variables.

reaching investors promptly. This study has examined the association between firms' dissemination decisions about financial information and the COE. Overall, the findings support the idea that firms can use Twitter to improve the communication with investors, which reduces the time and energy of acquiring news about the firm, reduces information asymmetry and enhances investor recognition and firm visibility.

More specifically, the study has made a number of theoretical contributions. Firstly, using the implied COE as a proxy for COE, we find that *iDisc* is significantly and negatively associated with the COE. The results indicate that firms which rely more on *iDisc* to voluntarily disseminate financial information have significantly lower COE financing. This finding is robust for firm-specific risk, information intermediaries, analysts' forecast biases, earnings surprise and information intermediaries. Second, we have shown that the effect of *iDisc* is more pronounced for less-visible firms that are smaller in size, have a low analyst following and a limited number of investors. These findings are consistent with the investor recognition notion that highly visible firms are likely to have a lower impact on the COE since their information is already disseminated through other information intermediaries. Third, we have extended our analyses to examine whether the magnitude of the news, when missing earnings forecasts or conveying more negative or positive meanings, would affect our main findings. We find that *iDisc* is negatively associated with the COE even after considering the magnitude of the news. Finally, the results are robust to different *iDisc* and COE measures. As a sensitivity check, we have: (i) used *iDisc* with hyperlinks to reflect the diffusion and spread of information; and (ii) applied the modified price-earnings growth (R_{PEG}) model, as an alternative measure of the COE. The findings from these sensitivity analyses support our main results, suggesting that extensive use of *iDisc* reduces the COE. These findings motivate firms' managers to use Twitter to disseminate financial information in order to enhance firms' information environment and transparency and also to reduce the uncertainty and agency problem between informed and uninformed investors, which limits the firm's accessibility to lower external financing costs. These findings also shed light on firm managers' concerns about firm visibility by showing that disseminating financial information on Twitter can benefit these firms and reach a wider number of investors. Managers should also consider engaging in iDisc activity to reduce the COE even when news about the firm is not favourable.

Future research could examine other markers and how decision investments are affected by local social media practices. Similarly, other social media and big data platforms that have different characteristics to that of Twitter (e.g. Facebook or LinkedIn) could be considered. It would also be of interest to examine not just dissemination but also user engagement and whether the sectors in which firms operate and the business norms in them play a role in social media investor engagement. We also acknowledge some limitations regarding the variable measurements, such as using *SILICON* as a proxy for technology firms, which is subject to some limitation as not all technology firms' headquarters are located in Silicon Valley. However, our study provides comprehensive evidence that using social media as a dissemination channel can have a real effect on the capital market.

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Figure 1

Research model

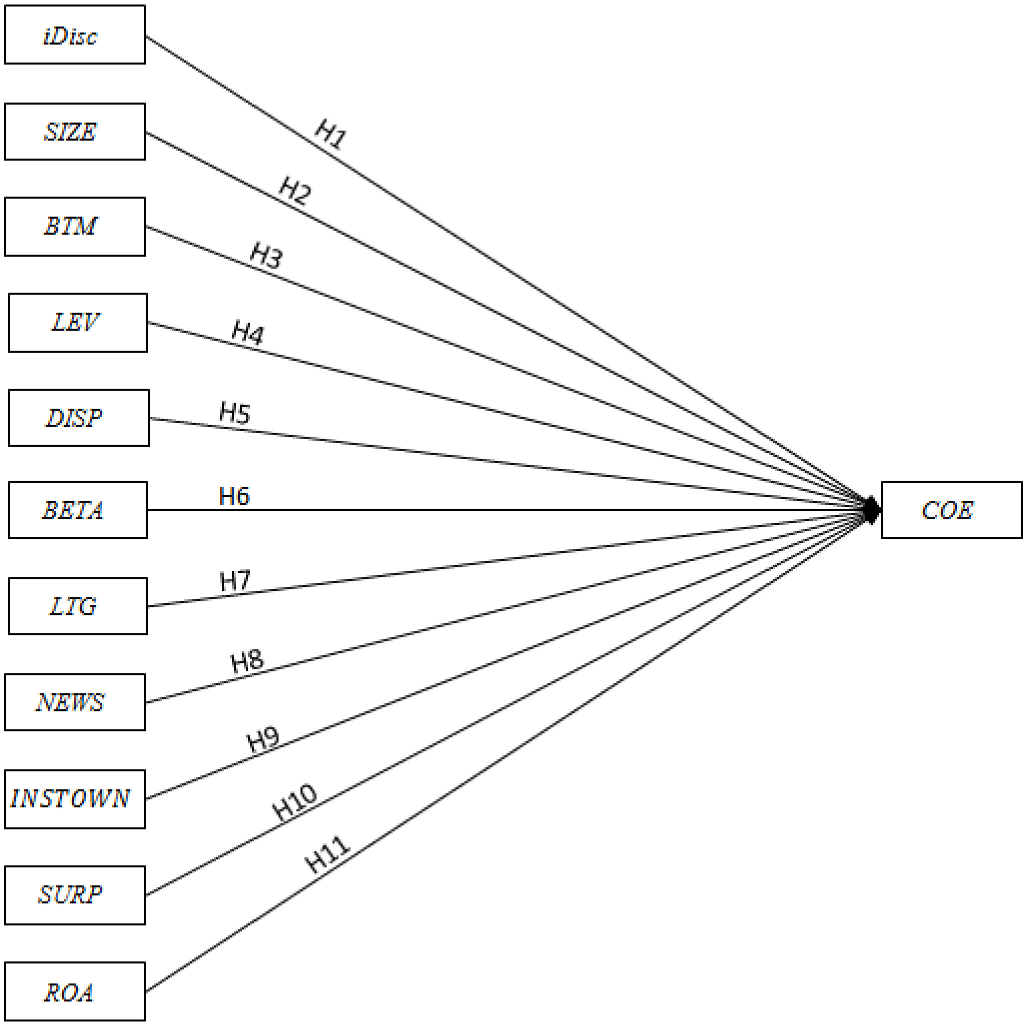

Table 1
Summary of association between research model variables

Variables	Direction	Related studies
Dissemination of financial information (iDisc)	-	
Firm size (*SIZE*)	-	(See Botosan, 1997; Dhaliwal et al., 2006; Gebhardt et al., 2001; Mangena et al., 2016)
Book-to-market ratio (*BTM*)	+	(See Easton, 2004; Hail & Leuz, 2006; Fama & French, 1992; Gode & Mohanram, 2003; Mangena et al., 2016)
Financial leverage (*LEV*)	+	(See Cao et al. 2015; Dhaliwal et al, 2006; Fama & French, 1992; Modigliani & Miller, 1958)
Analyst forecast dispersion (*DISP*)	+	(See Dhaliwal et al. 2016; El Ghoul et al., 2018; Gode & Mohanram, 2003; Guedhami & Mishra, 2009; Kothari et al., 2009a)
Systematic risk (*BETA*)	+	(See Botosan, 1997; Botosan et al., 2011; Cao et al., 2015; El Ghoul et al., 2011)
Long-term growth rate (LTG)	+	(See Cao et al., 2015; Chen et al., 2011; Gode & Mohanram, 2003; Guedhami & Mishra, 2009)
Press coverage (*NEWS*)	+/-	(See Fang & Peress, 2009; Jung et al., 2014; Kothari et al., 2009a; Niessner & So, 2017)
Institutional holdings (*INSTOWN*)	-	(See Attig et al., 2012, 2013; Elyasiani & Jia, 2010; Elyasiani et al., 2010)
Earnings surprise (*SURP*)	+	(See El Ghoul et al., 2011; Kim & Shi, 2011; Mikhail et al., 2004; Rogers et al., 2009)
Return on assets (*ROA*)	-	(See Bowman, 1979; El Ghoul et al., 2018; Francis et al., 2005; Gode & Mohanram, 2003)

Table 2

Firm Twitter and *iDisc* Characteristics

Panel A: Twitter and iDisc Adoption among Firms in the Sample

Type	% to Firms with Twitter Account
Firms use *iDisc* once	66%
Firms use *iDisc* for three years	44%

Notes: Panel (A) provides the percentage of firms in NASDAQ, with a Twitter account, which uses *iDisc* once and for three years.

Panel B: Average iDisc use among Firms

Years	Average *iDisc* Tweets	% of *iDisc*			
		Financial Reporting (FR)	Financing (Fin)	Financial Term (FT)	Financial Ratio (FR)
2009	1	70%	11%	22%	18%
2010	3	68%	10%	25%	18%
2011	6	68%	10%	27%	27%
2012	6	70%	8%	23%	16%
2013	8	69%	8%	23%	14%
2014	11	76%	6%	17%	11%
2015	13	77%	5%	18%	11%
Average	7	73%	7%	21%	15%

Notes: Panel (B) reports the average number of *iDisc* tweets per year and summary statistic of the percentage use of *iDisc* components across the sample period.

Table 3

Industry Summary of *iDisc*

Fama-French 12-Industry classification	Percentage of *iDisc* based on	
	Industry	Total *iDisc*
Food, Tobacco, Textiles, Apparel, Leather, Toys	15.3%	1.2%
Cars, TV's, Furniture, Household Appliances	16.5%	1.0%
Machinery, Trucks, Planes, Office Furniture, Paper, Com Printing	33.6%	4.1%
Oil, Gas, and Coal Extraction and Products	43.8%	0.3%
Chemicals and Allied Products	48.1%	1.2%
Software, Computers, and Electronic Equipment	54.0%	37.2%
Telephone and Television Transmission	39.4%	4.1%
Utilities	29.8%	0.7%
Shops Wholesale, Retail, and Laundries, Repair Shops Services	16.2%	4.1%
Healthcare, Drugs and Medical Equipment	36.4%	17.0%
Mines, Construction, Bldg Material, Transportation, Hotels, Business Service, Entertainment	36.0%	28.9%

Notes: Table 3 provides summary statistics of firm use of *iDisc* across Fama-French 12-industry classification excluding financial industry for NASDAQ firms with Twitter accounts from 2009 to 2015.

Table 4

Descriptive Statistics for all the Variables

Variables	N	Mean	Median	Min	Max	SD
COE	1358	0.051	0.044	0.003	0.161	0.034
iDisc	4131	0.968	0.000	0.000	5.690	1.332
iDisc_NUMBER	4131	7.418	0.000	0.000	295	20.699
SIZE	4030	20.247	20.148	14.594	26.992	1.744
BTM	3806	-1.374	-1.029	-18.364	1.703	2.132
LEV	4006	0.160	0.065	0.000	0.758	0.205
DISP	3298	0.162	0.093	0.016	0.846	0.185
BETA	3046	1.191	1.153	0.385	2.197	0.402
LTG	3940	0.094	0.150	-1.000	0.667	0.297
NEWS	4111	5.557	5.434	2.639	8.354	1.042
INSTOWN	3649	0.769	0.829	0.000	1.707	0.315
SURP	3082	0.365	0.088	-4.529	2.996	0.927
ROA	3912	-0.073	0.022	-1.142	0.216	0.274

Notes: Table 4, summary statistics are presented for COE estimates, *iDisc* and other explanatory variables for NASDAQ firms with Twitter accounts from 2009 to 2015. See Appendix (A and B) for definitions of the variables. The table presents the number of observations (N), mean (Mean), median (Median), minimum (Min) and maximum (Max) values and standard deviation (SD). To control for outliers, we use a winsorizing level of 2.5^{th} to 97.5^{th} percentiles for all variables except for *iDisc*, *BTM* and *INSTOWN*.

Table 5

Pearson and Spearman Correlations for the Cost of Equity (COE), *iDisc* and Other Explanatory Variables

Variables	*COE*	*iDisc*	*SIZE*	*BTM*	*LEV*	*DISP*	*BETA*	*LTG*	*NEWS*	*INSTOWN*	*SURP*	*ROA*
COE	1	-0.120***	-0.297***	0.415***	0.1020***	0.010	0.183***	-0.097***	-0.058*	-0.074**	0.151***	-0.094***
iDisc	-0.085***	1	0.079*9	0.012	0.055	-0.027	0.070**	-0.034	0.082**	-0.046	0.045	-0.106***
SIZE	-0.323***	0.125***	1	-0.421***	0.150***	0.199***	-0.199***	-0.090***	0.642***	0.178***	-0.325***	0.377***
BTM	0.145***	-0.041**	-0.153***	1	0.016	0.000	0.196***	-0.264***	-0.099***	-0.078**	0.25***	-0.416***
LEV	0.110**	-0.006	0.143***	-0.132***	1	0.102***	-0.015	-0.168***	0.171***	0.004	0.005	-0.239***
DISP	0.043	0.005	0.140***	-0.106***	0.087***	1	0.042	0.002	0.256***	0.094***	-0.054	-0.008
BETA	0.231***	-0.004	-0.121***	0.068***	0.089***	0.035*	1	0.045	-0.049	0.024	0.198***	-0.197***
LTG	0.242***	-0.031*	0.228***	0.034**	-0.054***	-0.138***	-0.024	1	-0.055	0.031	0.062**	-0.084**
NEWS	-0.095***	0.098***	0.63***	-0.143***	0.125***	0.178***	0.029	0.098***	1	0.084**	-0.081**	0.087**
INSTOWN	-0.163***	-0.008	0.472***	0.049***	0.030*	0.002	-0.026	0.192***	0.237***	1	-0.174***	0.064*
SURP	0.184***	0.013	-0.330***	0.140***	-0.029	-0.036*	0.151***	-0.128***	-0.089***	-0.274***	1	-0.268***
ROA	-0.245***	-0.043***	0.422***	0.109***	0.007	-0.182***	-0.110***	0.358***	0.158***	0.383***	-0.209***	1

Notes: Table 5 presents the Pearson and Spearman correlation between COE, *iDisc* and explanatory variables for NASDAQ firms with Twitter accounts from 2009 to 2015. See Appendix (A and B) for the descriptions of the variables. ***, **, * present the statistically significant level at 1%, 5% and <10% respectively.

Table 6

The Impact of *iDisc* on Cost of Equity (COE)

	(1) (OLS)	(2) (2SLS)
iDisc	-0.0014**	-0.0028*
	(0.0007)	(0.0016)
SIZE	-0.0041***	-0.0043***
	(0.0011)	(0.0013)
BTM	0.0127***	0.0130***
	(0.0017)	(0.0023)
LEV	0.0389***	0.0339***
	(0.0076)	(0.0081)
DISP	0.00136	0.0003
	(0.0065)	(0.0089)
BETA	0.0099***	0.0106***
	(0.0031)	(0.0039)
LTG	0.0438***	0.0444**
	(0.0148)	(0.0190)
NEWS	0.0036**	0.0062***
	(0.0017)	(0.0017)
INSTOWN	0.0008	-0.0005
	(0.0043)	(0.0051)
SURP	0.0026	0.0039**
	(0.0017)	(0.0018)
ROA	0.0132	0.0254
	(0.0208)	(0.0195)
Year Effect	Yes	Yes
Industry Effect	Yes	Yes
Firm Effect	Yes	Yes
Wu-Hausman Test		0.215
Constant	0.105***	0.0980***
	(0.0196)	(0.0248)
Observations	829	551
R^2	0.476	0.472

Notes: This table presents the regression results of the impact of *iDisc* on *COE*. The sample consists of nonfinancial firms in NASDAQ with Twitter accounts from 2009 to 2015. See Appendix (A and B) for definitions of the variables and measurements. Column (1) represents the results from pooled cross-sectional regression clustered at the firm level (OLS). Column (2) reports the results from the second stage of the 2SLS regression model. *, **, *** signify the significance level at 10%, 5% and 1% respectively. Robust standard errors are in parentheses.

Table 7

The Effect of *iDisc* on Cost of Equity (COE) for High- and Low-Visible Firms

	High SIZE		Low SIZE		High ANALYSTS	Low ANALYSTS	High LNOWN	Low LNOWN
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	(OLS)	(2SLS)	(OLS)	(2SLS)	(OLS)	(OLS)	(OLS)	(OLS)
iDisc	-0.0006	0.0018	-0.0023**	-0.0039*	-0.0012	-0.0026***	-0.0008	-0.0017*
	(0.0009)	(0.0018)	(0.001)	(0.0021)	(0.0011)	(0.0009)	(0.0011)	(0.0009)
SIZE	-0.0037**	-0.0051**	-0.0081***	-0.0075***			-0.0033**	-0.0053***
	(0.0015)	(0.0021)	(0.0024)	(0.0026)			(0.0016)	(0.0014)
BTM	0.0075***	0.0053	0.0147***	0.0177***	0.0121***	0.0162***	0.0108***	0.0124***
	(0.0025)	(0.0032)	(0.0019)	(0.0023)	(0.0028)	(0.0019)	(0.0027)	(0.0022)
LEV	0.029***	0.0126	0.0413***	0.0427***	0.0352***	0.0444***	0.0314**	0.0383***
	(0.0102)	(0.0119)	(0.0092)	(0.0107)	(0.0131)	(0.0091)	(0.0145)	(0.0088)
DISP	-0.0046	-0.0053	0.0094	-0.0028	-0.0033	-0.0104	-0.0149	0.0099
	(0.0066)	(0.0111)	(0.0123)	(0.0123)	(0.0081)	(0.0099)	(0.0096)	(0.0081)
BETA	0.0033	0.0071	0.0138***	0.0155***	0.0084*	0.0141***	0.0066	0.0102***
	(0.0043)	(0.0068)	(0.0038)	(0.0043)	(0.0045)	(0.0041)	(0.0055)	(0.0035)
LTG	-0.0209	0.0005	0.0589***	0.0568***	0.0368	0.0617***	0.0293	0.0506***
	(0.0201)	(0.0280)	(0.0172)	(0.0204)	(0.0319)	(0.0167)	(0.0258)	(0.0168)
NEWS	0.0027	0.0048**	0.0053***	0.0068***	0.00155	0.0005	0.0046**	0.0037*
	(0.0020)	(0.0022)	(0.002)	(0.0020)	(0.0018)	(0.0021)	(0.0023)	(0.0019)
INSTOWN	-0.0005	0.00156	0.0048	-0.0006	0.0070	-0.0030	0.0089	-0.0024
	(0.0057)	(0.0068)	(0.0064)	(0.0069)	(0.0053)	(0.0060)	(0.0065)	(0.0054)
SURP	0.0022	0.0032	0.00181	0.0035*	0.0014	0.0027	0.0052**	0.0013
	(0.0041)	(0.0039)	(0.0018)	(0.0019)	(0.0034)	(0.0019)	(0.0022)	(0.0019)
ROA	0.0494**	0.0340	-0.0002	0.0220	0.0452**	-0.0193	0.0383	0.0066
	(0.0213)	(0.0280)	(0.0225)	(0.0234)	(0.0185)	(0.0223)	(0.0317)	(0.0222)
LNOWN							-0.001	0.0021**
							(0.0013)	(0.0009)
ANALYSTS					-0.0051	-0.0055		
					(0.0044)	(0.0043)		
Year Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Wu-Hausman Test		0.278		0.263				
Constant	0.111***	0.136***	0.163***	0.139***	0.0293*	0.0516***	0.0833***	0.133***
	(0.0289)	(0.0421)	(0.0420)	(0.0455)	(0.0160)	(0.0167)	(0.0275)	(0.0264)
Observations	365	219	464	332	383	446	258	570
R^2	0.350	0.334	0.537	0.546	0.400	0.519	0.604	0.475

Notes: This table presents the regression results from estimating our base Model (1) of the impact of *iDisc* on *COE* based on firm visibility. The sample consists of nonfinancial firms in NASDAQ with Twitter accounts from 2009 to 2015. See Appendix (A and B) for definitions of the variables and measurements. The full sample is divided into subsamples based on firm size, analyst following and number of investors. Firm observation placed on the 4th (1s, 2d, 3d) quartile level is designated as high visible (low visible) firms. Columns (1-4) represent the relation based on firm size (*SIZE*). Analyst following (*ANALYSTS*) is added to columns (5-6) and number of investors (*LNOWN*) is added to columns (7-8). The coefficient estimates are based on pooled cross-sectional regression clustered at the firm level (OLS), except for models (2&4), which apply 2SLS model (2SLS). *, **, *** represent the significance level at 10%, 5% and 1% respectively. Robust standard errors are in parentheses.

Table 8

News Magnitude of *iDisc* and Cost of Equity (*COE*)

	Model (2) News magnitude (OLS)	Model (3) News contents (OLS)
iDisc	-0.0013*	-0.0019**
	(0.0007)	(0.0008)
|SURP|	0.0007	
	(0.0006)	
NegSURP	0.0012	
	(0.0019)	
*|SURP| * iDisc*	0.0002	
	(0.0003)	
*|SURP| * NegSURP*	-0.0002	
	(0.0006)	
TONE		0.0002
		(0.0002)
*TONE * iDisc*		0.00003
		(0.00004)
SIZE	-0.0037***	-0.0042***
	(0.0012)	(0.0011)
BTM	0.0121***	0.0127***
	(0.0016)	(0.0018)
LEV	0.0331***	0.0390***
	(0.0075)	(0.0075)
DISP	0.0041	0.0015
	(0.0076)	(0.0065)
BETA	0.0105***	0.0097***
	(0.0032)	(0.0031)
LTG	0.0547***	0.0441***
	(0.0161)	(0.0148)
NEWS	0.0028	0.0036**
	(0.0018)	(0.0017)
INSTOWN	0.0013	0.0009
	(0.0044)	(0.0043)
SURP		0.0027
		(0.0017)
ROA	-0.0081	0.0141
	(0.0174)	(0.0209)
Year Effect	Yes	Yes
Industry Effect	Yes	Yes
Firm Effect	Yes	Yes
Constant	0.101***	0.107***
	(0.0197)	(0.0196)
Observations	891	829
R^2	0.470	0.478

Notes: The table reports the effect of *iDisc* on implied cost of equity capital after controlling for news magnitude and information content. The sample consists of nonfinancial firms in NASDAQ with Twitter accounts from 2009 to 2015. See Appendix (A and B) for definitions of variables and measurements. Model (2) presents the results after adding news magnitude based on earnings surprise variables. Model (3) includes the tone (*TONE*) of *iDisc* text, in which a tweet could convey the meaning of news reported and its interaction with *iDisc* (*TONE* * *iDisc*). *TONE* is measured based on positive and negative words from the Loughran and McDonald lists. The coefficient estimates are based on pooled cross-sectional regression clustered at the firm level (OLS) and *, **, *** represent the significance level at 10%, 5% and 1% respectively. Robust standard errors are in parentheses.

Table 9

Applying Alternative Measures of *iDisc* and Cost of Equity (COE)

	(1) COE (OLS)	(2) R_{PEG} (OLS)
iDisc_Hyperlink	-0.0015**	
	(0.0007)	
iDisc		-0.003**
		(0.0014)
SIZE	-0.0041***	-0.0053***
	(0.0011)	(0.0018)
BTM	0.0130***	0.0017
	(0.0017)	(0.0024)
LEV	0.0409***	-0.0211
	(0.0076)	(0.0149)
DISP	0.00071	0.0192*
	(0.0062)	(0.0112)
BETA	0.0099***	0.0205**
	(0.0031)	(0.0088)
LTG	0.0518***	0.120***
	(0.0155)	(0.0352)
NEWS	0.0037**	0.0059***
	(0.0017)	(0.0022)
INSTOWN	0.00057	-0.0281***
	(0.0044)	(0.0099)
SURP	0.0028	0.0089**
	(0.0018)	(0.0037)
ROA	0.0179	-0.145***
	(0.0189)	(0.0334)
Year Effect	Yes	Yes
Industry Effect	Yes	Yes
Firm Effect	Yes	Yes
Constant	0.104***	0.181***
	(0.0196)	(0.0381)
Observations	829	1,550
R^2	0.483	0.283

Notes: This table represents the regression results from estimating our base Model (1) using different measures of *iDisc* and COE. The sample consists of nonfinancial firms in NASDAQ with Twitter accounts from 2009 to 2015. See Appendix (A and B) for definitions of variables and measurements. We use *iDisc* with hyperlink in column (1). In column (2), we use R_{PEG} as an alternative measure of the cost of equity. The coefficient estimates are based on pooled cross-sectional regression clustered at the firm level (OLS) and *, **, *** represent the significance level at 10%, 5% and 1% respectively. Robust standard errors are in parentheses.

Table 10

Robustness Tests for Including Other Additional Variables

	(1) COE (OLS)	(2) COE (OLS)	(3) COE (OLS)	(4) COE (OLS)
iDisc	-0.0015**	-0.0019**	-0.0015**	-0.00141**
	(0.0008)	(0.0009)	(0.0007)	(0.0007)
SIZE	-0.0031**	-0.0048***	-0.0044***	-0.0041***
	(0.0012)	(0.0016)	(0.0011)	(0.0011)
BTM	0.0129***	0.0171***	0.0117***	0.0121***
	(0.0016)	(0.0018)	(0.0017)	(0.0017)
LEV	0.0352***	0.0419***	0.0373***	0.0379***
	(0.0078)	(0.0086)	(0.0077)	(0.0076)
DISP	0.0079	-0.0049	0.0015	0.0008
	(0.0075)	(0.0077)	(0.0065)	(0.0065)
BETA	0.0126***	0.0044	0.0103***	0.0099***
	(0.0034)	(0.004)	(0.0031)	(0.0031)
LTG	0.0560***	0.073***	0.0467***	0.0457***
	(0.0170)	(0.0195)	(0.0147)	(0.0146)
NEWS	0.0031	0.0043*	0.0038**	0.0038**
	(0.0020)	(0.0023)	(0.0018)	(0.0017)
INSTOWN	0.0009	-0.0003	0.0013	0.0009
	(0.0050)	(0.0066)	(0.0042)	(0.0042)
SURP	0.0042**	0.0024	0.0030*	0.0026
	(0.0018)	(0.0029)	(0.0017)	(0.0017)
ROA	-0.0015**	0.0612***	0.0161	0.0149
	(0.0008)	(0.0166)	(0.0225)	(0.0214)
ACCRUAL	0.0032			
	(0.0098)			
ADVERTISING		-0.0028		
		(0.008)		
SILICON		0.00311		
		(0.0035)		
CEOAGE		0.0017		
		(0.0025)		
MMT6			-0.0076***	
			(0.0019)	
MMT12				-0.0071***
				(0.0019)
Year Effect	Yes	Yes	Yes	Yes
Industry Effect	Yes	Yes	Yes	Yes
Firm Effect	Yes	Yes	Yes	Yes
Constant	0.0686***	0.117***	0.113***	0.108***
	(0.0208)	(0.0263)	(0.0199)	(0.0195)
Observations	634	443	813	827
R^2	0.443	0.552	0.493	0.486

Notes: This table presents the regression results from estimating our base Model (1) by including additional robustness tests for our selected sample. The sample consists of nonfinancial firms in NASDAQ with Twitter accounts from 2009 to 2015. See Appendix (A and B) for definitions of the variables and measurements. Column (1) controls for information quality by adding discretionary accrual (*ACCRUAL*) as a control variable. Column (2) reports the regression after adding variables that relate to social media adoption (*ADVERTISING*, *SILICON*, and *CEOAGE*). We have also added price momentum in the last 12 months and 6 months in columns (3&4) to control for the sluggishness of analysts' forecasts. The coefficient estimates are based on pooled cross-sectional regression clustered at the firm level (OLS) and *, **, *** represent the significance level at 10%, 5% and 1% respectively. Robust standard errors are in parentheses.

Appendix A: Variables Definition and Measurements

Variable	Definition	Measurement	Source
Dependent Variables			
COE	Cost of equity	The average expected rate of return of R_{OJ}, R_{MPEG}, R_{CT} and R_{GLS} minus the risk-free rate.	Bloomberg
R_{PEG}	Cost of equity	The expected rate of return based on Easton (2004)	Bloomberg
Independent Variables			
iDisc	Firm's financial Tweets	Log of 1 plus the number of financial tweets including (financial reporting, Financial term, Financial ratio and Financing terms tweets)	Twitter API and Manual collection
iDisc_Hyperlink	Firm's financial Tweets with hyperlink	Log of 1 plus the number of financial tweets that contain hyperlink	Twitter API and Manual collection
iDisc_NUMBER	Firm's financial Tweets	The number of financial tweets	Twitter API and Manual collection
SIZE	Firm size	Natural logarithm of market value of equity	Bloomberg
BTM	Book value to market ratio	Natural logarithm of book value to market value ratio	Bloomberg
LEV	Financial leverage	Long term debt scaled by market value	Bloomberg
DISP	Analysts' forecast dispersion	Standard deviation of 1 year ahead earnings per share forecast	Bloomberg
BETA	Firm beta	Slope coefficient of 60 months market return	Bloomberg
LTG	The consensus long term growth forecast	The average long-term growth forecast in June or two-year consensus EPS forecast minus one-year consensus EPS forecast divided by the mean of one-year consensus EPS forecast	Bloomberg
NEWS	News coverage	Natural logarithm of number of news articles about the firm	LexisNexis
INSTOWN	The percentage of Institutional ownership	The proportion of the shares outstanding owned by institutions	Bloomberg
SURP	Earning surprise	Natural logarithm of the consensus earnings forecast for forthcoming fiscal year - actual earning / stock price	Bloomberg
ROA	Return on assets	Income before extraordinary items divided by book value of assets (total common equity)	Bloomberg
ANALYST	Analyst following	Natural log of number of analysts making an earnings forecast	Bloomberg
LNOWN	Number of investors	Natural logarithm of number of shareholders	Bloomberg
|Surp|	Absolute earning surprise	Absolute value of the consensus earnings forecast for forthcoming fiscal year - actual earning / stock price	Bloomberg
NegSURP	Negative earnings surprise	Indicator variable equal to 1 if earning surprise is below zero and 0 otherwise	Manually computed

ACCRUAL	Discretionary accruals	The difference between discretionary accruals based on Jones model and firm's corresponding discretionary accruals	Bloomberg
ADVERTISING	Advertising intensity	Advertising expenses divided by total sales	Bloomberg
SILICON	Silicon Valley	Indicator variable equal to 1 if firm is located in Silicon Valley and 0 otherwise	DataStream
CEOAGE	CEO age	Indicator variable equal to 1 if CEO age is below the median value and 0 otherwise	DataStream
MMT(6)	Price momentum	Compounded rate of return of the previous 6 months	Manually computed
MMT(12)	Price momentum	Compounded rate of return of the previous 12 months	Manually computed

Appendix B: Cost of Equity Measurements

COE estimates	Formula
R_{OJ} Ohlson and Juettner-Nauroth (2005) employed by Gode and Mohanram (2003) model	$$R_{OJN} = A + \sqrt{A^2 + \left(\frac{E_t(EPS_{t+1})}{P_t^*}\right)(g_2 - g_{lt})}$$ $$A = 0.5\left(g_{lt} + \frac{DPS_{t+1}}{P_t^*}\right)$$ EPS $_{t+1}$ = The median of earning forecast per share for the next year in June DEPS $_{t+1}$ = Dividend per share for the next Year computed as pay-out ratio for firms with positive earning or 6% of ROA g_2 is the short-term earnings growth rate of EPS_{t+1} and EPS_{t+2} or long-term growth rate of analysts' forecasts. This model requires $EPS_{t+1} > 0$ and $EPS_{t+2} > 0$. g_{lt} is the difference between 10-year treasury bonds yield and 3%
R_{MPEG} Modified Easton (2004) cost of equity module by Gode and Mohanram (2003)	$$P_t = \frac{E_t(EPS_{t+1})}{R_{MPEG}} + \frac{E_t(EPS_{t+1})E_t[g_{st} - R_{MPEG} \times (1 + \mathrm{FDIV})]}{R_{MPEG}^2}$$ P_t = firm price in June in each year FEPS=the median of earning forecast per share for the next i year at time t FDIV=forecast dividend pay-out ratio equal to $\left(\frac{\mathrm{DPS}}{\mathrm{EPS}}\right)$ DPS=dividend per share EPS= earnings per share The model assumes positive FEPS but if EPS is negative, FDIV is measured by replacing EPS by 6% of return on asset.
R_{CT} Claus and Thomas (2001)	$$P_t^* = B_t + \sum_{i=1}^{5}\frac{[FEPS_{t+i} - R_{CT} \times B_{t+i-1}]}{(1 + R_{CT})^i} + \frac{[FEPS_{t+5} - R_{CT} \times B_{t+4}] \times (1 + g_{lt})}{(R_{CT} - g_{lt})(1 + R_{CT})^5}$$ The model measures earnings per share for the next 5 years by using analyst forecasts. The forecasted earnings for the 4th and 5th years are estimated by the earning forecast of the 3rd year and growth rate of long term earnings. If the long-term growth rate is not found, EPS_{t+2} and PS_{t+3} are used. The long term abnormal earning growth rate is measured as 10 years Treasury bonds minus 3%. Clean surplus relation is used to estimate future book value ($B_{t+i-1} = B_t + EPS_{t+1} - DPS_{t+1}$). Estimating future dividend is estimated by multiplying earnings per share by pay-out ratio ($DPS_{t+1} = EPS_{t+1} \times FDIV$).
R_{RGLS} Gebhardt, Lee, and Swaminathan (2001)	$$P_t^* = B_t + \sum_{i=1}^{T-1}\frac{[FROE_{t+i} - R_{GLS}] \times B_{t+i-1}}{(1 + R_{GLS})^i} + \frac{[FROE_{t+T} - R_{GLS}] \times B_{t+T-1}}{(1 + R_{GLS})^{T-1}R_{GLS}}$$ The model measures forecasted return on equity by using analyst forecasts for the next 3 years. From the 4th year to T number of years, ROE is forecasted using linter interpolation to industry median based on 10 years historical industry specific ROE. In case the industrial ROE is lower than the risk-free rate, Industrial ROE would be replaced with risk free rate (Liu, Nissim, and Thomas, 2002). It is also assumed that t = 12, which indicates that ROE

	remains constant afterwards. The research also assumes that firms are classified under 48 industries as defined by Fama and French (1997). Additionally, the model applies a clean surplus to estimate forecasted book values of equity. Where, $B_{t+i-1} = B_t + EPS_{t+1} - DPS_{t+1}$ $DPS_{t+1} = EPS_{t+1} \times FDIV$
COE	The cost of equity measured by the average of four measures ($R_{OJ,}$ $R_{MPEG,}$ R_{CT} and $R_{GLS,}$) minus risk-free rate.
R_{PEG} Easton (2004) Price Earnings Growth Model	$$P_t^* = \frac{FEPS_5 - FEPS_4}{R_{PEG}^2}$$ The first model is for the short-term horizon and the second is for the long-term horizon. P_t = = firm price in June of each year, FEPS $_t$ = median of earning forecast at year *t*.