**Who's On and Who's Not on Social Media?**

**An Empirical Study of Twitter Adoptions**

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## Abstract

We explore the factors that motivate firms to adopt and use Twitter, the most widely used social media platform. Firms can potentially benefit from social media to gain greater visibility, reduce information asymmetry, or improve investor and customer relations. We hypothesize that product market characteristics, degree of information asymmetry, and the visibility of the firm are among the major reasons for Twitter adoptions, and also consider the determinants of voluntary disclosures. A comprehensive analysis of the economic determinants of Twitter adoptions is rare, in part, because of the significant hurdles involved in data collection. We address all firms that created a Twitter account between 2006 and 2017, comprising 202,799 firm-quarters and 18.62 million tweets. Using survival analysis models, we find that more visible firms - characterized by large firm size, frequent press coverage, large analyst following, high institutional ownership, and low information asymmetry are more likely to adopt and use Twitter. We interpret this evidence to imply that firms that are actively followed by the press and the investing public see a greater need to control the information environment. Perhaps not surprisingly, we also find that B2C companies are significantly more likely and quicker to adopt Twitter than B2B firms and that B2C firms with higher information asymmetry are even more likely to adopt Twitter than B2B firms. Litigation risk and firm age are also influential determinants of Twitter adoption.

## 1. Introduction

The rapid advance of information technology and brisk social media participation by business entities are topics of growing interest for academics and the regulators. On April 2, 2013, the SEC endorsed the legitimacy of social media by declaring that *"companies can use social media outlets like Facebook and Twitter to announce key information in compliance with Regulation Fair Disclosure (Regulation FD) so long as investors have been alerted about which social media will be used to disseminate such information."*[1] Studies report that a growing number of firms take advantage of Twitter or other social media platforms as information disclosure and dissemination channels. As examples, firms use Twitter to attenuate the adverse impact of product recalls (Lee, Hutton and Shu, 2015); to reduce information asymmetry (Blankespoor, Miller, and White, 2014); and to strategically under-disseminate when earnings are less stellar than expected and the magnitude of the bad news is worse (Jung, Naughton, Tahoun, and Wang, 2018). Another large strand of literature examines the link between Twitter activities (not necessarily firm-initiated) and economic outcomes, suggesting that the Twitter volume and sentiment are informative about future value-relevant events such as earnings, revenues, and stock price changes (e.g., Bartov, Faurel, and Mohanram, 2018; Bollen, Mao, and Zeng, 2011; Mao, Wei, Wang, and Liu, 2012; Curtis, Richardson, and Schmardebeck, 2016; Tang 2018).

Nevertheless, how pervasively firms embrace social media platforms to capitalize on their potential benefits has not been widely researched. This is noteworthy because a significant fraction of firms still does not use social media to help disseminate information. For example, Jung et al. (2018) report that as of January 2013, 47% and 42% of the large firms (S&P 1500) use Twitter and Facebook, respectively. According to our updated data, the proportion of S&P 1500 firms having a Twitter account rose to 64.8% by 2017, whereas only 42% of the smaller, non-S&P 1500 firms have a Twitter account in 2017. In 2017, 49.7% of all U.S. firms (including those outside the S&P 1500) have a Twitter account, and 96% of those firms also tweet. It is, therefore, useful to understand what factors motivate some firms to adopt social

[1] See http://www.sec.gov/News/PressRelease/Detail/PressRelease/1365171513574.

media, but not other firms. A comprehensive analysis of the economic determinants of Twitter adoptions is scarce, in part, because of the significant hurdles involved in data collection. For this reason, past studies have focused on a specific industry (e.g., Blankespoor 2014), a short time frame and larger firms (e.g., Jung et al. 2018).[2] Furthermore, the primary objectives of both Blankespoor et al. (2014) and Jung et al. (2018) are not about examining the determinants of Twitter adoption.

In this research, we explore the determinants of a firm's decision to create and use a Twitter account for information dissemination and stakeholder engagement. Our study uses Twitter because it is the most widely used social media platform, surpassing Facebook, LinkedIn, YouTube, and other social media sites (Jung et al., 2018). Our sample comprises all firms that have adopted Twitter between the inception of Twitter (October 2006) and the end of 2017, including 6,974 unique publicly-listed firms, among which 2,535 are Twitter- adopting firms. The sample addresses 202,799 firm-quarters (57,814 Twitter firm-quarters) and 18.62 million tweets by firms, collected from the official primary Twitter[3] sites between 2006 and 2017. Because we include all firms that have had a Twitter account since the Twitter inception, our study is the most comprehensive study to date, to the best of our knowledge, which explores firms' use of Twitter accounts and their Tweet volume.

This study addresses four main research questions. First, because Twitter adoption and use are voluntary, we ask whether the economic factors known to influence firms' voluntary disclosures are also relevant for Twitter adoption. This is an open question because Twitter is primarily a mechanism for *dissemination* of existing information rather than a medium of new information *disclosure* (Miller and Skinner 2015, Jung et al. 2018). Nevertheless, we consider proxies for incentives and costs of voluntary disclosures, which likely play a role in a firm's decision to have a Twitter presence. Such proxies include competition, litigation risk, business uncertainty, and asset structure. The next three inquiries concern

[2] Blankespoor et al. (2014) examines technology firms. Jung et al. (2018) model the cross-sectional determinants of Twitter usage for any time between the first quarter of 2010 to the first quarter of 2013 (one observation for each firm) for S&P 1500 firms.

[3] We define a primary Twitter account as the main official Twitter account that appears on the webpage of a firm. Notice that a firm may have secondary Twitter accounts. Section 4 explains the process used for identifying primary Twitter accounts. This study considers only primary Twitter accounts.

interactions with two key stakeholders of the firm: investors and consumers. The first of such hypotheses extends the literature concerning the *visibility* of the firm. In particular, Bushee and Miller (2012) argue that firms face significant challenges in improving visibility and attracting investors because institutional investors and security analysts tend to neglect firms with low visibility. Accordingly, less visible firms that have difficulty reaching a broad network of investors can have additional incentives to devote resources on improving investor relations and visibility. Blankespoor et al. (2014) also note that the press is biased toward coverage of highly visible firms and suggest that the extent of dissemination via Twitter can differ by the degree of firm visibility.[4] Therefore, less visible firms can have a stronger incentive to adopt Twitter to improve firm visibility. A contrary proposition is that more visible firms, as they are subject to frequent press coverage and public scrutiny, may see a greater need to be more proactive and to be in control of their messaging and information dissemination. If so, more visible and actively followed firms are more likely to adopt Twitter.

The next hypothesis concerns whether firms adopt Twitter to reduce information asymmetry. This hypothesis builds on Blankespoor et al. (2014) who hypothesize that dissemination of news via Twitter can help mitigate information asymmetry by bypassing intermediaries and brining information directly to a broader set of investors. If so, firms that have greater information asymmetry can have a stronger incentive to adopt Twitter to lower the asymmetry.

Lastly, the potential benefits of social media presence from interactions with stakeholders go beyond improving investor relations or communicating with investors. A Twitter platform enables a firm to spread information quickly and directly to a vast network of consumers (Lee, et al. 2015). Such a feature is especially advantageous for B2C (business-to-consumer) firms to facilitate product introduction, advertising, customer service, customer engagement, and to expand the customer base (Tang 2018). As a result, we hypothesize that B2C firms, in general, have a stronger incentive than B2B (business-to-business) firms to adopt and use Twitter. We also examine whether B2C firms with high

[4] They are careful not to suggest that Twitter impacts firm visibility, however.

information asymmetry are more likely to adopt Twitter to reap the dual benefits of directly engaging with both customers and investors.

We use duration models[5] – Weibull and Cox models – for our econometric analysis. We adopt the duration models rather than the standard logit or probit models for two reasons. First, whether a firm would adopt Twitter is a continuing event because firms that have not adopted as of the end of the data can still adopt Twitter in later periods. Second, the probability that a firm would adopt Twitter can be duration-dependent, rising or falling over time. Duration models are flexible enough to permit both circumstances and account for time-varying covariates.

Results indicate that economic factors that are known to affect voluntary disclosures, such as competition (a proxy for proprietary cost), litigation risk, business uncertainty, and asset structure influence firms' propensity to adopt Twitter adoption. Among such factors, litigation risk has a first-order effect on Twitter adoption, indicating that firms with high litigation risk have a higher propensity to adopt Twitter. Other factors, such as competition, business uncertainty, or asset structure, have some but less material impact on the tendency to adopt Twitter.

Results also suggest that the propensity to adopt Twitter is higher for more visible firms than for less visible ones based on widely used proxies of firm visibility. More specifically, Twitter adoption is more likely for larger firms and those with higher institutional holdings, more analyst following, and more frequent press coverages. The finding that the results are consistent across all proxies of firm visibility suggests that larger and more visible firms find the Twitter dissemination medium to be more useful. We also find that firms with lower information asymmetry, measured by bid-ask spread, have a higher tendency to adopt Twitter. Thus, the incentive to lower information asymmetry does not appear to be an influential driving force of Twitter adoption, perhaps contrary to conventional wisdom. This outcome, when considered in conjunction with the finding that larger and more visible firms tend to adopt

[5] See Section 3 for more details on the survival analysis models used in this study.

Twitter, is consistent with a characterization that firms adopt Twitter to be more proactive in controlling the information flow and managing the way the firms communicate with the stakeholders.

To examine the last research question, we classify the sample firms into three categories: business-to-consumer (B2C), business-to-business (B2B), and firms engaging in both B2B and B2C businesses ("Both"). We report the following main findings. First, perhaps not surprisingly, B2C firms are significantly more likely than the B2B firms to adopt Twitter. This is especially true during the initial wave of Twitter adoptions between 2007-2011 when B2C firms were 74.7% more likely to adopt Twitter than B2B firms. Stated differently, consumer-oriented firms were more likely and quicker to adopt Twitter than non-consumer-oriented firms. Furthermore, high information asymmetry (measured by the bid-ask-spread) is substantially more relevant for the B2C firms than for the other firms in adopting Twitter. We find qualitatively similar results when we measure consumer-oriented businesses using industry indicator (Retail industry) or using a measure of advertising intensity. Such findings suggest that consumer-oriented firms find greater potential benefits from using Twitter as a medium of interacting with customers and investors.

Our study contributes to the existing literature in three ways. First, this is the first study, to our knowledge, that examines comprehensively the economic factors that influence the firm's decision to adopt Twitter, using a representative sample that includes virtually all firms that have and have not adopted Twitter between 2007-2017. It is useful to understand such economic factors because, aside from inherent interest, an analysis of the Twitter-using firms without considering such determinants can induce selection bias. In particular, a study that examines the impact of tweets needs to consider the determinants of adopting Twitter. Otherwise, it can make an incorrect conclusion if the outcome variable is impacted by Twitter determinants rather than by the tweets themselves.

Second, our paper adds to the growing body of contemporary research seeking to inquire how firms seek to control social media to improve their information environment and to tailor their messages their advantage (Blankespoor et al., 2014; Lee et al. 2015; Jung et al., 2018). Our study not only corroborates such studies suggesting that firms adopt Twitter to reap potential economic benefits but also indicates that firms that need to be more responsive to external stakeholders tend to adopt Twitter. Miller and Skinner (2015) observe that firms have lost a certain amount of control of their information environments with the advent of social media. Our study finds that more visible firms are more proactive in utilizing social media to take control of their information environment. Finally, we demonstrate that firms using different business models have different incentives to adopt Twitter. An implication from Tang (2018) and others is that Twitter especially relevant for B2C firms than for B2B firms. We indeed document evidence suggesting that the B2C firms have stronger incentives to adopt Twitter to establish a direct communication channel with consumers and investors and to lower information asymmetry.

The rest of the paper is organized as follows: We develop the test hypotheses extending the previous literature in Section 2. We explain the research design in Section 3. Section 4 contains the data collection procedures, the sample, and variable measurement. We present the results in Section 5 and conclude in Section 6.

## 2. Literature Review and Hypotheses Development

This study builds on four studies, Bushee and Miller (2012), Blankespoor et al. (2014), Jung et al. (2018), and Tang (2018), but with a different emphasis. First, except for Blankespoor et al. (2014) and Jung et al. (2018), studies are relatively silent on why some firms elect to use social media to interact directly with the stakeholders. This is notable because there is still a significant number of firms that do not use social media, although most of the previous research documents potential benefits rather than pitfalls of using social media. Our data indicate that Twitter adoptions accelerated between 2008 and 2011 but since then slowed down considerably, leaving 50% of the U.S. firms still without a primary Twitter account as of 2017. Therefore, it is of interest to understand what factors motivate some firms to adopt and use social media, but not for other firms.

Our hypotheses address four streams of literature on information dissemination through social media. The first is a large set of literature regarding firms' voluntary disclosures. Beyer et al. (2010) show that voluntary disclosure provides approximately 66% of accounting-based information, whereas mandatory disclosure offers less than 12% of the total accounting-based information used by investors. Nevertheless, Miller and Skinner (2015) distinguish information disclosure (what to disclose and when to disclose) from dissemination (what medium or channel to use to distribute the chosen information). Jung, et al. (2018) also note that dissemination is different from disclosure and propose that a firm's decision to disseminate information through social media may be viewed as an extension of its disclosure strategy. If Twitter primarily serves as a mechanism of dissemination rather than a medium of revealing new information, then it is unclear whether the determinants of voluntary disclosures are relevant. The voluntary disclosure literature is relevant, however, as firms do not have to broadcast using Twitter, and there are costs and benefits that firms must weigh before they decide to adopt Twitter.

Extant studies suggest that there are abundant potential benefits from providing more expansive voluntary disclosures.[6] First, research indicates that a higher disclosure level can reduce information risk and cost of capital (Barry and Brown 1985, Piotroski 1999, Botosan and Plumlee 2002).[7] Such benefits are nontrivial because even a few basis point reduction in the cost of capital can add substantial market value to a firm. Similarly, research suggests that decreased disclosures exacerbate the adverse selection problem among traders and manifest as a high bid-ask spread, low market depth, and share turnover (Diamond and Verrecchia 1991, Kim and Verrecchia 1994, Verrechia and Weber 2006). Healy, Hutton, and Palepu (1998) find that firms that dramatically expand disclosure exhibit lower bid-ask spreads, greater stock liquidity and higher analyst following compared to their industry counterparts.[8]

[6] See Healy and Palepu (2001), Beyer et al. (2010), and Graham et al. (2005) for a more detailed review of literature related to benefits and costs of voluntary disclosure decisions.
[7] Botosan and Plumlee (2002) report that the cost of equity capital decreases in the level of disclosure of the annual report but increases in the level of timely disclosures.
[8] In addition to lower information asymmetries, higher-level disclosures are documented to reduce uncertainty and volatility of the firm's stock (Billings et al. 2015).

Despite the significant benefits of disclosure, the cost associated with revealing proprietary information is one of the most important reasons why firms are reluctant to make voluntary disclosures (Verrecchia, 1983; Hou and Robinson, 2006). The principal argument is that firms' disclosure of private information can undermine their competitive position in product markets (Verrecchia, 1983; Darrough and Stoughton, 1990; Darrough, 1993; Gigler, 1994). Similarly, competitors can use Twitter feeds to track the firm's activities and find out what consumers say about the company's products and services. Competitors can also hire "product reviewers" to slander the company. A recent paper by Hosseini, Jostova, Philipov, and Savickas (2020) emphasizes this slander aspect of the "social media risk" in their study of asset-pricing implications of social media. In sum, an extensive use of Twitter can inform the competitors to the detriment of the firm. Following previous research, we use a measure of product market competition (Herfindahl-Hirschman index: HHI) as a proxy for proprietary costs involved in firms' disclosures. We note, however, that measuring proprietary costs using SIC-based concentration measures is among the major challenges in the disclosure research (Beyer et al. 2010).[9] Heitzamn, Wasley, and Zimmerman (2010) contend that there are conflicting theoretical predictions on how competition impacts disclosure, and there is a lack of evidence in the empirical literature on the impact of proprietary costs on disclosure.

Another perspective of the impact of market competition is that in a competitive environment, firms are likely to take advantage of any small opportunities that could provide an advantage over other competitors. As such, firms facing more intense competition can have a greater incentive to adopt Twitter. Thus, ex-ante, it's unclear how market competition affects a firm's decision to use Twitter.

Litigation risk is another primary consideration in firms' disclosure decisions and can have two opposing effects. On the one hand, a delayed or untimely disclosure of bad news can increase the likelihood of shareholder lawsuits. For this reason, studies argue that expanded disclosures, especially

[9] Ali, Chen, and Radhakrishnan (2009) report that proxies using public company database such as COMPUSTAT can lead to significant measurement error for the actual intensity of product market competition. Such measurement errors may have contributed to mixed results (e.g., Berger and Hann 2007).

early and timely ones, can limit the exposure to litigation risk (Skinner 1997, Baginski, Hassel, and Kimbrough 2002, Field, Lowry, and Shu 2005). On the other hand, litigation risk potentially reduces firms' incentives to provide discretionary, particularly forward-looking information (Beyer et al. 2010).[10] From an empirical standpoint, Kim and Skinner (2012) find that the predictive power of litigation risk measures based on industry classification is minimal, but substantially improves when they are used jointly with measures of firm size, growth, and stock return volatility. Accordingly, we supplement the proxy for litigation risk with such measures. To summarize, our first hypothesis asks whether the well-known determinants for voluntary disclosure are also relevant to voluntary dissemination through Twitter.

**Hypothesis 1:** Ceteris paribus, the determinants of voluntary disclosures are irrelevant for the firms' decision to use Twitter as a mechanism for dissemination.

The next hypothesis concerns the visibility of the firm. Blankespoor et al. (2014) note that traditionally, firms have relied upon third-party intermediaries to disseminate information and lower the information barrier. The press coverages, however, tend to focus on highly visible firms (which are typically large-capitalization firms) as they attract a larger readership (Miller 2006). Bushee and Miller (2012) show that less visible firms, as they have difficulty reaching a broad network of investors, invest resources to improve investor relations. Such firms subsequently improved media following, institutional investor following, and market value. Bushee, Core, Guay, and Hamm (2010) report that broader coverage by the press reduces the bid-ask spread. Blankespoor et al. (2014) find that the reduction of the bid-ask-spread following a Twitter adoption holds more strongly for firms that receive less press coverage. They interpret the results to be consistent with the less visible firms having a greater need for the additional dissemination platform. Jung et al. (2018) suggest that Twitter, because it enables a firm to control the timing and the amount of information disclosure, can be used to broaden dissemination and overcome a lack of investor attention.

[10] For example, Rogers and Van Buskirk (2009) report that firms reduce disclosures after class-action lawsuits, suggesting that litigation risk decreases firms' incentives to disclose, notwithstanding the increased protections under the Private Securities Litigation Reform Act of 1995.

While these studies point to a prediction that the incentive to adopt Twitter is higher for less visible firms, we postulate that highly visible firms can also have a strong incentive to adopt Twitter. This is because greater visibility does not necessarily attract favorable press coverages and public attention. As a result, there is a need to be more proactive in dealing with the media and external stakeholders, so that the firms can react quickly and to alter the tone of the conversation (Jung et al. 2018, Huan, Parbonneti, Redigolo, and Zhang 2019). Huan e al. (2019), for example, report that when the LIBOR scandal was revealed by the press, suspect banks issued a barrage of tweets to alleviate the adverse impact and have succeeded in moderating the negative stock price impact of the news. Accordingly, the social media strategy is likely to be an integral part of the overall investor relations strategy of more visible firms. Furthermore, the setup and maintenance costs for a social media presence are likely to be smaller for more visible, typically larger firms than for the smaller, less visible firms. The following hypothesis applies.

**Hypothesis 2:** Ceteris paribus, the propensity to adopt Twitter is not different between more and less visible firms.

A third hypothesis, which extends Blankespoor et al. (2014), addresses firms' information asymmetry and disclosure/dissemination strategy. Blankespoor et al. (2014) hypothesize that further dissemination of firm-initiated news via Twitter can help mitigate information asymmetry by allowing information to reach a broader set of investors directly. Such an effort can result in increased liquidity. Blankespoor et al. (2014) find that dissemination of firm-initiated news via DAITs (direct-access information technologies) is associated with lower abnormal bid-ask spreads and greater abnormal depths, consistent with a reduction in information asymmetry. Lin, Prabhala, and Viswanathan (2009) argue that relational aspects of online social networks can create value by mitigating the information asymmetry between borrowers and lenders. Using the data from a peer-to-peer lending network, their analysis indicates that online social networks can exert peer pressures and increase the verifiability of network ties, thereby alleviating the information asymmetry in peer-to-peer lending markets. If Twitter can help reduce information asymmetry, firms with higher information asymmetry have a greater incentive to adopt Twitter than those with lower information asymmetry. Thus, the next hypothesis, stated in the null form, applies.

**Hypothesis 3:** Ceteris paribus, the degree of information asymmetry does not influence the firms' propensity to adopt Twitter.

Fourth, most of the accounting research understandably focuses on the impact of social media on the firm's relations with the investing community. To understand the incentives for adopting Twitter holistically, we consider another critical stakeholder of the firm, namely, the consumers. Potentially substantial benefit can come from the firms' ability to engage directly with the customers in a manner that is not possible through traditional information channels (Miller and Skinner 2015). A Twitter platform enables a firm to disseminate product-related information quickly and directly to a wide network of customers (Lee et al. 2015). Such a feature is especially useful for firms whose main customers are consumers, namely, the B2C (business-to-consumer) firms. Tang (2018) suggests that Twitter user comments, once summarized at the firm level, are incrementally informative, especially for firms whose major customers are consumers than for business-to-business (B2B) firms. The implication from Tang (2018) is that B2C firms, in general, can have a stronger incentive to adopt and use social media (Twitter platform) because they can benefit more from using the Twitter platform.

Active participation in social media is not always a winning strategy, however. Once created, a firm must invest in resources and manpower to ensure continuous monitoring and fast response. Lee, Qui, and Whinston (2018) point out that online platforms can cause unintended consequences as they are susceptible to manipulations by firms and other interested parties. The authors suggest that social media and review websites are exposed to sentiment manipulations, spams, and fake reviews, thereby deteriorating information quality. Furthermore, despite the perceived benefits of using Twitter in consumer-oriented companies, whether and how tweeting affects product demand remains inconclusive (Gong, Zhang, Zhao, Jiang 2017). Using Facebook, for example, Lee, Hosanger, and Nair (2018) report that brand personality content is associated with higher levels of consumer engagement with a message, while directly informative content is associated with higher engagement levels when provided in conjunction with the attributes related to brand personality. The preceding points suggest that social media is not necessarily beneficial to all consumer-oriented enterprises. In sum, the hypothesis, stated in the null form, is as follows:

**Hypothesis 4:** Ceteris Paribus, the propensity to adopt Twitter is not different between the B2C firms and B2B firms.

The alternative hypothesis is that the B2C firms and "BOTH" types that serve both consumers and businesses are more likely to adopt Twitter than the B2B firms. Finally, since dissemination through Twitter can lower information asymmetry, an incentive to reduce information asymmetry can be an additional impetus for B2C firms contemplating adopting Twitter. We, therefore, test the potential moderating effect of information asymmetry on consumer-oriented firms.

## 3. Research Design

We use survival (duration) models to examine the decision to create a Twitter account. Duration models are appropriate for our research objective for two reasons. First, our sample is right-censored because whether a firm would adopt Twitter is a continuing event (firms which have not adopted as of the end of the data can still adopt Twitter in later periods). Second, the probability that a firm would adopt Twitter can be duration-dependent, rising or falling over time. Duration models, as they can accommodate time-varying covariates, are more suitable than the static choice models such as logit or probit. The latter models are less suitable as they essentially test whether a firm has a Twitter or not, rather than when a firm adopts Twitter at different points in time.

In a duration analysis, the survival function gives the probability that a subject will survive beyond time t. In our setting, the survival function S (t) represents the probability that a firm does not open a Twitter account beyond time t, denoted by the current quarter. The hazard function h (t) represents the instantaneous rate at which events occur – the event being the creation of a Twitter account by a firm. The relationship between hazard function and survival function is characterized by

$$h\,(t) = f\,(t)/S\,(t), \tag{1}$$

where $h\,(t_i)$ is designated as the hazard rate, representing the instantaneous conditional probability of event occurring given that a firm has survived (not adopted Twitter) up to t. The duration model is parametrized as

$$h\,(t_i) = h_0\,(t_i)\, e^{(X'\beta)} \tag{2}$$

where $h_0\,(t)$ denotes some baseline hazard function for which some functional form is assumed. t is the response (time to event), $X'\beta$ is the set of covariates which also affect the event.

There are different approaches to modeling the survival data. We consider two parametric models based on two distributional assumptions on $h_0\,(t)$: Cox and Weibull. [11] The Cox proportional-hazard model (Cox 1972) makes no assumption on the shape of $h_0\,(t_i)$ over time t and implies that the conditional probability of Twitter adoption is not time-dependent since the beginning of Twitter. The Weibull distribution allows monotonically increasing or decreasing duration dependence of the hazard ratio, where the baseline hazard rate is $h_0\,(t) = pt^{p-1}$ and p is a shape parameter to be estimated. The hazard, or the likelihood of Twitter adoption, is rising if $p > 1$, constant if $p = 1$, and declining if $p < 1$. Our data suggests the shape of the hazard function in our sample to be that $p > 1$. Nevertheless, the Cox semi-parametric model has some advantages over other models. It requires minimal assumptions about the distribution of event times; allows for modeling time-varying variables; and is robust, so that the results generated will "closely approximate the correct parametric model" (Kleinbaum and Klein 2005, 96). The Cox model provides no direct estimate of $h_0(t)$—the baseline hazard.[12]

[11] Survival analysis is also known as duration modeling. Exponential, gamma, log normal are some of the other distributions which can be used to model the hazard function. However, the shape of the hazard function most closely resembles a Weibull distribution with p>1. Therefore, we use Weibull models in our survival analysis modeling.

[12] Formally, the function $h_0$ (t) is not directly estimated, but it is possible to recover an estimate of the cumulative hazard $h_0(t)$ and, from that, an estimate of the baseline survivor function $S_0(t)$.

Following the hypotheses outlined in Section 2, we express the covariates of the duration model, $X'\beta$, as follows.

$$X'\beta = f\,(Disclosure,\ Visibility,\ Asymmetry,\ B2B,\ BOTH,\ Controls) \tag{3}$$

where *Disclosure* designates a set of variables representing disclosure costs concerning Hypothesis 1. *Visibility* is a set of proxies for the firm's visibility relating to Hypothesis 2. *Asymmetry* represents the bid-ask spread, a proxy for information asymmetry (Hypothesis 3). The indicator variables *B2C* and *BOTH* designate firms whose customers are consumers and those whose customers are both consumers and businesses, respectively (Hypothesis 4). Finally, the set of *Control* variables account for the determinants of voluntary disclosures. Below is a more detailed description of the variables. Appendix A provides precise definitions of all variables. We use quarterly data to estimate the duration model.

**Disclosure and Proprietary Cost:** We use the Herfindahl-Hirschman Index (HHI) delineated by 2-digit SIC industries as a measure of market competition. HHI is a commonly-used proxy for the degree of market competition in the industry (Verrecchia and Weber, 2006; Heitzman et al., 2010). Following Francis et al. (2004), we use an indicator variable (*Litigation*) designating litigation-prone industries as a proxy for litigation risk. Kim and Skinner (2012) report that the predictive power of the litigation risk proxy increases when used jointly with measures of firm size (log of beginning total assets: *Firm_Size*), growth (book-to-market: *BTM*), and stock volatility (standard deviation of stock returns over the previous 250 days: *Ret_Volatility*). We, therefore, include the three variables.

Notice that stock return volatility is also a proxy for information uncertainty in the market, and the book-to-market ratio also reflects financial statement informativeness and complexity (Tasker 1998; Bushee et al., 2003).[13] Extant literature also indicates the relevance of asset structure and profit structure of firms. As examples, firms that participate in frequent and substantial financial transactions such as mergers and acquisitions, generally have more complex information to communicate (Bushee et al.,

[13] We do not use management guidance as a control variable because we view it to be an outcome variable derived from other determinants of voluntary disclosure behavior. The inclusion or exclusion of management forecast has an immaterial impact on the overall conclusions.

2003). Such firms have a high proportion of recorded intangible assets (*Intangibles*) on their books (goodwill, purchased intangibles, etc.), but the financial reports may not reflect the full import of these intangible assets. Such firms, therefore, can have a greater incentive to use Twitter as a dissemination mechanism to reach out to investors. Similarly, current earnings of firms that belong to high technology (hi-tech) industry (Chen et al., 2002) are likely to be less informative, motivating the inclusion of an indicator variable for hi-tech industries (*Silicon*). This is likely to be more pronounced when firms experience rapid growth or incur high R&D expenses as a proportion of total assets (*R&D_Expense*). However, these firms also introduce new and innovative products and services and may want to create barriers to entry (Gaver and Gaver, 1993). The larger the growth opportunities, the more reluctant managers are to reveal information that could dissipate the value of these opportunities. Thus, it is unclear ex-ante whether hi-tech industry firms are more or less likely to use Twitter.

**Firm Visibility:** We use five proxies for firm visibility. First, following Bushee et al. (2010) and Bushee and Miller (2012), we consider the extent of press coverages, designated as *Media_Following*. This is the frequency of news articles in a given quarter (natural Log of one plus the number of news articles written about a firm during the preceding quarter) taken from Lexis-Nexis. Following Bushee et al. (2010), we assume that all articles carried on press release wires (e.g., PR Newswire, Business Wire) are firm-initiated disclosures. We consider all other articles as press-initiated (*Media_Following*). To distinguish media following from firms' own press releases, we also include the frequency of firm-initiated press releases (*Firm_Press_Release*). The next three measures are based on Blankespoor et al. (2014): 1) firm size (log of beginning total assets) which is the primary measure for firm visibility in Bushee and Miller (2012); 2) the number of shareholders holding the stock (Merton 1987, Blankespoor et al. 2014: *Num_Shareholders*); and 3) institutional holdings (LeHavy and Sloan 2008: *Inst_Ownership*).[14] The fifth proxy is the analyst following (natural log of one plus the number of analysts: *Analyst_Following*), which represents not only the degree of the firm's visibility but also the demand for information.

[14] Blankespoor et al. (2014) use the number of institutions holding a firm's share. We also use the log of market capitalization rather than total assets with immaterial changes in our results.

**Information asymmetry:** Following Blankespoor et al. (2014) and Bushee et al. (2010), our primary measure of information asymmetry is the bid-ask spread. We measure abnormal bid-ask spread (*BidAskSpr*) of quarter t as the average daily spread during quarter t, where the daily spread is calculated as the difference between the offer price and bid price, divided by the closing price (Bushee et al. 2010). Notice that the measures of uncertainty and asset characteristics are also related to information asymmetry, namely, the proportion of recorded intangible assets (*Intangibles*), R&D expense as a proportion of total assets (*R&D_Expense*), stock return volatility (*Ret_Volatility*), growth opportunity (*BTM*).

**B2B and B2C firms:** We use a proprietary database provided by uscompanydata.com that classifies about 30 million U.S. businesses into three categories: business-to-business (B2B), business-to-consumer (B2C), or BOTH. We perform the mapping between this dataset and the Compustat using phone numbers and the company names provided in both databases. When we cannot match a sample firm, we use the corresponding 4-digit SIC classification of which the firm is a member. The majority of the Compustat sample firms are classified as doing business in BOTH (52%), whereas B2B and B2C firms represent about 31.6% and 16.4%, respectively. Firms classified as B2B constitute the benchmark sample. We also use two alternative measures to designate consumer-oriented businesses: the Fama-French retail industry classification (*Retail*)[15] and advertising intensity (advertising expenditure/total assets of the preceding quarter: *Advertising_Expense*). We prefer the B2C-B2B designation because there are many other companies/industries which deal with retail consumers than those in the Fama-French retail classification. The use of advertising expenditures to classify B2C vs. B2C companies is subject to endogeneity because how much to spend on advertising and whether to disclose the expenditure is discretionary.[16] Liang (2019) hypothesizes and finds that when advertising rivalry is more intense, firms with high advertising

[15] We classify all firms in SIC 5200-5999 as Retail, although Fama-French separately classify SIC 5800-5890 as retail restaurants.

[16] When firms elect not to disclose such expenditures (such as Apple Inc.; Liang 2019), they are misclassified, and their omission can cause a selection bias.

expenses are less likely to disclose advertising expenditures to stave off competitors' overreaction. B2C classification based on all companies does not involve such selection biases.

**Other control variables:** Because Twitter operation involves costs, it is ideal to have a control variable representing the cost of creating and administering Twitter. As such information is unobservable, we use variables representing firm performance and the strength of the balance sheet. Profitable firms and cash-rich firms are more likely to afford the cost of operating Twitter. As Twitter adoption is costly and optional, debt-ridden, or cash-strapped firms can be less inclined to adopt Twitter. We use the accounting rate of return (*ROA*) as a measure of firm performance following Jung et al. (2018) and include cash-to-assets (*Cash*) and financial leverage (*Leverage*) as control variables. The latter two variables represent the strength of the balance sheet. We also consider the CEO age, but do not use the variable in the main model because the variable requirement reduces the sample size by 45%. We do find, however, that firms with younger CEOs are more likely to adopt Twitter in the smaller sample including the CEO age.

## 4. Sample

### 4.1. Sample Collection

Firms use a plethora of social media platforms, although Twitter and Facebook[17] are the two most popular and widely used ones. Jung et al. (2018) find that by early 2013, the corporate adoption rate of Twitter surpassed the rate for Facebook. Also, Facebook information or user engagement is not public, whereas Twitter conversations are public. In its 2017 10-K filing, Twitter disclosed that it had 330 million average monthly active users (MAUs) in the three months ended December 31, 2017. New age hi-tech firms such as Google and Facebook have approximately 20.5 million and 13.5 million followers, respectively, and can tweet information and engage directly with them. For this reason, we focus on the use of Twitter.

We gather official company Twitter accounts and tweets, retweets, likes, and replies generated on these accounts. We verify all publicly listed U.S. firms from 2006 to 2017 as to whether they have an

[17] In addition to Twitter and Facebook, firms also use LinkedIn, Youtube, Pintinterst, and Instagram, to name a few others.

official Twitter account and use the Twitter Application Program Interface (API). We also retrieve the full text of each tweet for each firm in our sample. We focus only on the firms' primary Twitter accounts[18] in this paper. Below is a detailed data collection process.

We search the names of all publicly traded firms (from Compustat)[19] for the period 2006 to 2017 on three main search engines (Google, Yahoo, and Bing) and collect all the Twitter accounts associated with a company. We then feed the first two accounts identified via search engines to Twitter public API to retrieve the accounts' main descriptions (around 10,000 accounts). Next, we manually check the validity of each Twitter account by visiting each Twitter page and checking the link embedded in the account's page. We follow the Twitter verification method - the blue checkmark on the screen name of a firm's Twitter account indicates that the firm submitted documentation to Twitter and, hence, is the official Twitter account of the firm. For the Twitter accounts that did not have the verified sign, we check their (1) total followers (2) total tweets (3) type of activity (whether they are doing actual customer service, or they are providing information about corporate decisions or financial disclosure). To ascertain that the identified Twitter account is official, we also manually cross-check the websites of all publicly listed US firms with Compustat. We search the social media segments on their website and confirm that the Twitter accounts we collected match with those shown on the firms' websites[20]. This process also ensures that we do not miss any firm that has an official Twitter account. We designate these accounts as the primary official Twitter accounts. To ensure that we identified all of the Twitter accounts for each firm, we use Twitter search API and twitter search engine to find all the other accounts. We designate the Twitter accounts other than the primary account as secondary accounts. Finally, we check that the primary account is the oldest account among even unverified accounts. We use a combination of methods to collect total Tweets for

[18] In addition to having a primary Twitter account, some firms also create additional Twitter accounts for specific purposes such as different regions, investor relations, customer services, and recruitment.

[19] We exclude all firms which have total assets of less than 1 million USD, negative book equity, negative market values.

[20] On its website, a firm shows icons of all the social media platforms on which it has a presence (such as Twitter, Facebook, LinkedIn, Youtube). This icon is the link to the firm's official account.

each primary Twitter account as well as retweets and likes associated with each Tweet. First, account information was collected using "Account Look Up Twitter 2.0 API". The actual tweets, retweets, likes and comments were collected either by direct purchase from GNIP (official twitter vendor) or by using the "Stream API 2.0", which tracks accounts in real time as well as "Historical API", which only allows for 40 days look back. Our final Twitter data comprises of approximately 18.6 million tweets, 128.7 million retweets, 187.5 million likes, and 34.0 million replies by followers collected from the primary official Twitter sites of 2,535 unique firms.[21] This sample constitutes the most comprehensive, to the best of our knowledge, data of firms' Twitter accounts and Tweets.

We use quarterly data spanning the third quarter of 2006 to the last quarter of 2017 and collect financial data of firms from Compustat, stock return data from CRSP, analyst and guidance data from IBES, Institutional Ownership data from Thomson Reuters. We collect newspaper and press release data from LexisNexis. Our final sample comprises 202,799firm-quarters[22] and 6,974 unique publicly listed firms between the first quarter of 2006 to the last quarter of 2017. Owing to missing financial data and variables, the duration models are estimated using 115,428 firm-quarters.

**4.2 Descriptive Statistics**

[Insert Figures 1A & 1B here]

Figure 1A shows the number of firms creating Twitter accounts by year. Beginning with Starbucks, the first firm joining Twitter[23] in November 2006, [24] the number of firms adopting Twitter rapidly increased until it peaked in 2009 when 820 firms joined Twitter. Figure 1B shows the cumulative

[21] We are unable to find the official Twitter accounts for 11 firms even though there is a Twitter icon on their website. Therefore, we are unable to retrieve the Twitter account creation dates or the tweets for these firms and treat these firms as being without a Twitter account.
[22] We define a twitter firm-quarter as a quarter in which the firm maintains a primary Twitter account.
[23] As we only focus on primary official Twitter accounts of firms, a Twitter account refers to the primary official Twitter account of a firm.
[24] See https://twitter.com/starbucks.

proportion of firms that have a primary Twitter account delineated by large (S&P 1500), small (non-S&P 1500), and all firms.[25] As is evident from Figure 1B, Twitter adoption of S&P 1500 firms outpaced that of the smaller firms. By 2017, the percentage of S&P 1500 firms with a Twitter account is more than 50% higher than that of the non-S&P 1500 firms (64.8% versus 42.2%). As of 2017, 49.7% of *all* U.S. firms have a Twitter account, and 96% of those firms also tweet.

Because the characteristics of the firms adopting Twitter in earlier years (2007-2011) can be different from the late adopters (2012-2017), we also analyze the early adopters separately.

[Insert Figures 1C & 1D here]

Figures 1C and 1D display the yearly trend of the average and the total number of tweets made by firms on their primary Twitter accounts. As indicated in Figure 1C, the average number of tweets per firm rose about 38-fold, from 39 to 1,472 tweets per firm per year, between 2007 to 2017. Such evidence indicates that firms do find the Twitter platform useful and increase the usage each year. Not surprisingly, the total number of tweets by Twitter firms shows exponential growth until 2016, although it declined slightly in 2017.

[Insert Tables 2 A & B here]

Based on the Fama-French 48 industry classifications, Table 1A and Table 1B respectively show the ten industries with the highest (Table 1A) and the lowest (Table1B) proportion of Twitter adoption measured in firm-quarters in our sample. Most of the ten most Twitter-intensive industries are consumer-oriented, the Retail (Fama-French 42) being the most Twitter-intensive. Manufacturing and production industries comprise most of the ten least Twitter-intensive industries, such as Defense, Steel Works, Textiles, and Shipbuilding. In subsequent discussions, we refer to the firms which have a Twitter account as Twitter firms and those that do not have an account as non-Twitter firms.

[25] The delineation by S&P 1500 vs. non-S&P 1500 is because most prior studies use Twitter data for the S&P 1500 firms.

## 5. Results

### 5.1. Univariate results

[Insert Tables 2 and 3 here]

Table 2 shows the mean of firm characteristics for Twitter firm-quarters and non-Twitter firm-quarters and tests the difference between the two. Table 3 reports the extent of correlation among the explanatory variables. Twitter firm-quarters comprise approximately 30% of the sample. Notice that, unlike Table 1, Tables 2 and 3 and subsequent tables address the final sample of 115,428 firm-quarters that are subject to the duration model estimation.

On a univariate basis, there are significant differences between the two samples for most of the variables. Twitter firms tend to be larger and better performing (in terms of ROA), and also have more growth options (lower *BTM*), lower cash balance, and lower debt-to-total assets. They also have a higher proportion of intangible assets and higher industry concentration (*HHI*) in comparison to non-Twitter firms. But litigation risk is substantially higher for the Twitter firms. Twitter firms are also older, have higher institutional ownership, more intensive media and analyst following, a larger number of shareholders, and lower bid-ask-spread. Finally, Twitter-adopting firms are also more advertising-intensive but slightly less R&D-intensive, and exhibit lower return volatility than non-Twitter firms. The multivariate duration model reported below do not support all of the univariate comparisons, however.

### 5.2. Duration model outcomes

We consider both Cox and Weibull duration models but focus on the Weibull model, as the AIC criteria[26] suggest that Weibull distribution is a better fit. Most of the results are comparable, however, when we estimate the equation using the Cox proportional hazard model. We also estimate the Weibull

[26] AIC (Akaike Information Criteria) is a goodness-of-fit measure that combines the fit and the complexity (model parameters) and can be used to compare models that use the same variables and fit on the same data. The model with a smaller AIC value is considered to be better. AIC is calculated as $-2\ ln\text{L} + 2\text{k}$ where $-2\ ln\text{L}$ measures fit and 2k measures complexity.

model with and without frailty and find that the Weibull models with shared frailty do not converge using all of the explanatory variables in place. As such, we report results using the Weibull without frailty. We also include year fixed effects and industry fixed effects using Fama-French ten industry classification.

Tables 4 and 5 contain the estimate from the Weibull duration model. Table 4 addresses the full sample of adoptions between 2006-2017, whereas Table 5 considers a subsample for the initial wave of adoptions between 2006 and 2011. Results in both tables are consistent with each other, with a notable exception that the results for Hypothesis 2 (Firm visibility) and Hypothesis 4 (B2C vs. B2B) are substantially more pronounced for the earlier adoption period than for the full sample period.

[Insert Tables 4 and 5 here]

Table 4 reports the estimate using different combinations of the explanatory variables. Most of the differences regard how we classify consumer-oriented businesses. As examples, Columns (1) and (3) report results using the B2C-B2B-BOTH classification, whereas Columns (2) and (4) use two variables as a proxy for consumer-oriented businesses: advertising intensity (*Advertising_Expense*) and *Retail* industry (SIC 5200-5999) indicator. Notice that the shape parameter value "*p*" is significantly greater than unity in all models, implying a positive duration dependence, that is, the hazard rate (propensity to adopt Twitter) is increasing over time. This estimate supports using the Weibull model over the Cox model, although the Cox model estimates are generally consistent with those of the Weibull with slightly weaker significance levels. We discuss below how the estimates comport with the stated hypotheses. Notice that the signs of the coefficient estimates and the significance levels are generally consistent across different specifications.

**Proprietary Cost and Litigation Risk**

Despite the known limitations of using product market competition as a proxy for proprietary costs (Beyer et al. 2010), the Herfindahl-Hirschman index (HHI) continues to be a popular proxy for proprietary costs on firms' disclosure. If concerns of disclosing proprietary information negatively impact the firm's adoption and use of social media, the sign of the HHI coefficient (of industry concentration) is positive. The coefficient of HHI is often negative, however, and marginally significant (Column 1: -0.103, *t*=-1.35). Such evidence per se is not in sync with the hypothesis that firms in a more competitive industry are reluctant to adopt Twitter owing to proprietary cost concerns. The negative coefficient can alternatively be interpreted as a more competitive environment inducing firms to resort to Twitter to get ahead of the competition or as a response to competing firms adopting Twitter.

On the other hand, litigation risk (*Litigation*) has a strong positive relation to a firm's decision to join Twitter. The estimated coefficient of 0.259 (*t*=16.3) in Column 1 implies that firms in a more litigious industry are 29.5% more likely to adopt Twitter ($e^{0.259}$- $e^{0}$=0.295). Such evidence supports a characterization that firms use Twitter as a medium of transparency to preempt potential lawsuits. Other disclosure-related variables have significant effects on Twitter adoption, although not as strong as *Litigation*. In particular, extant research motivates the proportion of recorded intangible assets (*Intangibles*), stock return volatility (*Ret_Volatility*), a high-tech indicator (*Silicon*), and the book-to-market ratio (*BTM*) as proxies for the lack of financial statement informativeness and the inability of current period income to be a good measure of future income (Chen et al., 2002; Bushee et al., 2003; Tasker 1998). These studies suggest that firms with such characteristics have a greater incentive to reach out to investors and be more transparent about the firms' conditions. The estimates are broadly consistent with such a conjecture. The coefficient estimates on *Silicon*, *Intangibles*, and *Ret_Volatility* have the expected positive signs with relatively high significance levels with the exception of *Intangibles* (*t*=2.19, 1.32, and 4.76). The estimate on the book-to-market ratio (*BTM*) is negative and highly significant (-0.188, *t*= -13.5), suggesting that the incentive to adopt Twitter is greater for growth firms. Such results suggest that growth firms, high-tech firms, and those with lower financial statement informativeness have a greater incentive to broaden their information dissemination practices and communicate directly with investors. The combined evidence, taken together with the results for competition and litigation, is consistent with Twitter being adopted and used as a medium of dissemination (Miller and Skinner 2014, Jung et al. 2018), but not necessarily as a medium of new disclosure of potentially proprietary information.

**Firm visibility**

Hypothesis 2 concerns the visibility of the firm. The conventional wisdom is that less visible firms have difficulty reaching a broad network of investors, and thus, devote resources to improve investor relations and improve visibility and investor following (Blankespoor et al. 2014, Bushee and Miller 2012, Bushee, et al. 2010). If so, less visible firms have more significant incentives to take advantage of Twitter. The estimates for the proxies of firm visibility, however, indicate the opposite. In particular, the propensity to adopt Twitter is higher for firms that are larger (*Size:* 0.065, $t$=12.4), and those that receive more frequent press coverage (*Media_Following:* 0.088, $t$=20.9), broader analyst following (*Analyst_Following:* 0.119, $t$=12.2). All three determinants have strong significance levels. Institutional ownership (*Inst_Ownership*), the number of shareholders (*Num_Shareholders*), and the frequency of the firm's press releases (*Firm_Press_Release*) have insignificant t-values. Evidence regarding Institutional ownership and the number of shareholders is more compelling for the 2006-2011 initial wave of Twitter adoptions (Table 5). Observe that the estimates for the *Inst_Ownership* (0.103, $t$=1.78) and *Num_Shareholders* (0.026, $t$=4.29) are positive and have higher significance levels for this subsample than for the full sample.

Blankespoor et al. (2014) report that the reduction of the bid-ask-spread following a Twitter adoption holds more strongly for firms that receive less press coverage. They thus suggest that less visible firms have a greater need for additional dissemination platform such as Twitter. Jung et al. (2018) also suggest that Twitter, as it can be used to broaden dissemination, can overcome a lack of investor attention. The combined evidence above, when taken together, suggests that more visible firms have a stronger incentive to adopt Twitter than less visible firms.[27] We believe the results are sensible because greater visibility attracts both favorable and unfavorable press coverages and public attention. As a result,

[27] Notice that the evidence is not necessarily inconsistent with Jung et al. (2018).

there is a need for a firm to be more active in controlling the flow and content of information and react quickly and to alter the tone of the conversation (Jung et al. 2018, Huan, Parbonneti, Redigolo, and Zhang 2019).

**Information asymmetry**

Blankespoor et al. (2014) is one of the earliest research investigating the role of Twitter in disseminating information regarding market liquidity. Using a sample of technology firms, they examine the impact of using Twitter to send market participants links to press releases and find that this additional dissemination of firm-initiated news via Twitter is associated with lower abnormal bid-ask spreads and greater abnormal depths, consistent with a reduction in information asymmetry. Hypothesis 3 examines whether firms with higher information asymmetry has a stronger incentive to use Twitter as a medium of dissemination. Information asymmetry is measured primarily by the bid-ask spread (*BidAskSprd*), following Bushee et al. (2010), and Blankespoor et al. (2014). The negative estimated coefficient on bid-ask spread (-4.292, *t*=3.95) implies that firms which have lower bid-ask-spread, or higher liquidity, are more likely to adopt Twitter. Such a result is inconsistent with the conjecture that less liquid firms or those with higher information asymmetry are more inclined to adopt Twitter.

On the other hand, Twitter adoption positively correlates with variables that are associated with information asymmetry, such as growth opportunities (*BTM*), stock return volatility (*Ret_Volatility*), and intangible assets (*Intangibles*). R&D expense as a proportion of total assets (*R&D_Expense*), however, negatively correlates with Twitter adoption. In summary, the evidence is mixed regarding the hypothesis that the extent of information asymmetry influences Twitter adoption.

**B2B vs. B2C firms**

Hypothesis 4 rests on the assumption that different types of firms have different incentives to adopt Twitter. A Twitter platform is especially advantageous for B2C (business-to-consumer) firms to facilitate product introduction, advertising, customer service, customer engagement, and to expand the customer base. Accordingly, we hypothesize that B2C firms have a stronger incentive than B2B (business-to-business) firms to adopt and use Twitter.

Notice that firms classified as business-to-business (B2B) constitute the benchmark. In Table 4 Column 1, the estimate for B2C is 0.153 with an associated t-statistic is 5.89. The point estimate translates into a 16.5% higher propensity for B2C companies to adopt Twitter ($e^{0.153}$- $e^{0}$=0.165). More compelling evidence is in Table 5, which is based on the subsample for the period of 2006-2011. The estimate of 0.558 implies that B2C companies were 74.7% more likely to join Twitter during the earlier wave of Twitter adoptions. In sum, the estimates indicate that B2C companies found it potentially advantageous to deploy Twitter and did so quickly ahead of other companies in the earlier years of Twitter introduction. We also find it reasonable that firms that do both B2C and B2B businesses (BOTH) have smaller coefficient estimates of 0.052 and 0.247, respectively, in Table 4 and Table 5 (Column 1). Such estimates translate into 5.3% and 28.0% higher likelihood of Twitter adoption than the B2B companies.

Recall that we also use two alternative measures for consumer-oriented businesses: the Fama-French retail industry classification (*Retail*) and advertising intensity (advertising expenditure/total assets of the preceding quarter: *Advertising_Expense*). In Columns 2 and 3, both variables have a significant and positive coefficient with (Column 3) or without (Column 2) the B2C and BOTH indicators. We believe that the estimates based on the B2B-B2C classification are more reliable than those based on advertising expenditures because the latter is endogenous (i.e., a Twitter adoption can increase or decrease the advertising expenditures rather than the reverse).

Estimates in Columns 3 and 4 address the moderating effects of information asymmetry (measured by bid-ask-spread) on the type of customers. The estimates in Column 3 are significant and positive for the interaction terms *B2C*BidAskSprd* and *Retail*BidAskSprd*, with associated t-statistics of 7.79 and 4.76, respectively. The results indicate, therefore, that consumer-oriented firms with higher information asymmetry have a greater incentive to be present in social media such as Twitter. Such a result makes sense because Twitter can potentially bring dual benefits of improving customer relations and investor relations. In general, the early adopter sample provides more compelling evidence than the full sample. The magnitude of the coefficients, as well as the t-statistics, are higher for both *B2C*BidAskSprd* and *Retail*BidAskSprd* in Table 5 than in Table 4. A similar inference applies when *Retail* is used instead of B2C or BOTH (Column 4).

**Other determinants**

Social media presence is not costless. It can require substantial resources to create and maintain a Twitter or Facebook account. Therefore, cash-strapped firms or financially constrained (higher leverage) ones are less likely to maintain a Twitter account. The positive estimates for cash balance (*Cash*) and the negative estimate for *Leverage* are consistent with such a conjecture. It is unclear, however, why under-performing firms (measured by *ROA*) are more likely to adopt Twitter. Similar to the positive relationship between competition and Twitter adoption, this can indicate that underperforming firms have a greater incentive to engage in social media to find more profit opportunities. Finally, *Firm_Age* negatively correlates with Twitter adoption with a high t-statistic ($t$=33.81, Column 1, Table 4), indicating a strong association that younger firms tend to adopt Twitter significantly more than older firms.

**Results using actual tweets**

In Table 6, we examine how often the firms tweet, once they have decided to open a Twitter account. We employ the same set of the duration model determinants to explain the volume of Tweets (1+log(Tweets)) only for the firms that have a Twitter account. We estimate the model using the OLS regression. Notice that there is no need to estimate Heckman-style two-stage regressions because all known determinants of the first stage selection model (of what companies adopt Twitter) are present in the OLS regression. The standard errors are clustered by firm.

Coefficient estimates generally point to the same directions as with those of Tables 4 and 5, with a few exceptions. First, the frequency of tweets increases significantly with the influential determinants such as litigation risk, growth (BTM), *Media_Following*, *Analyst_Following*, *Num_Shareholders*, B2C, and *Retail*. Neither the bid-ask-spread nor its interaction with the B2C variable is significantly associated with the frequency of tweets, however. Finally, the estimate on firm performance (ROA) is positive (2.654, $t$=2.81). In the duration model, the estimate strongly negative (-2.494, $t$= -15.50), suggesting that underperforming firms are more likely to adopt Twitter. Such a contrasting result is consistent with a characterization that, once a firm establishes a Twitter account, they tend to tweet more about "good news" than about "bad news" (Jung. et al. 2018).

**Robustness Test**

We also estimate the duration model using the Cox proportional hazards model. The main difference between the Weibull and the Cox modes is that the former assumes time dependency of the hazards rate, whereas the latter does not. Nevertheless, the Cox model yields similar outcomes and conclusions as the Weibull model.[28]

Twitter account creation and its use can be two distinct events. In particular, there can be a significant time gap between these two events. In our sample, there is a gap of approximately 11.5 months, on average, between the date on which a firm creates a Twitter account, and it starts using it – and a small number of firms (about 4%) never use it. For such reasons, we estimate the model based on the time when a firm begins to use the Twitter account and find immaterial differences.

## 6. Conclusion

Social media have emerged as some of the most popular forms of dissemination of information and have been legitimized by the SEC as formal communication channels. There are costs and benefits in engaging with the stakeholder through social media, which explains why not all firms use this popular

[28] The results discussed in this section are untabulated but available upon request.

platform.  Few studies have, however, explored comprehensively the reasons why some firms use, whereas others don't use social media. Building on the existing studies of disclosure and dissemination, we examine what economic factors drive firms to adopt Twitter. Apart from the innate interest, the results of this study are useful to research that examines the impact of using Twitter. If a study does not account for the determinants of adopting Twitter, it can make incorrect conclusions because the outcome variables can be impacted by Twitter determinants, rather than by the tweets themselves. Depending on the research design, the key variables identified in this study can be used as instruments for the tweets or the presence of a Twitter, or as variables for the first stage selectivity regression of the Heckman-style models.

Primary findings that emerge from our analysis are as follows.  First, we find that more visible firms are more likely to adopt Twitter. This result can be at odds with the conventional notion that social media can be more beneficial to firms with low visibility than to highly visible firms. Our analysis does not necessarily refute the potential value of Twitter in improving firm visibility, however. Instead, it suggests that more visible firms have a greater need to engage stakeholders through social media than less visible firms. Second, we find that reducing information asymmetry as measured by bid-ask-spread is not a primary determinant of firms adopting Twitter, in the sense that more liquid firms are more likely to adopt Twitter.

Nevertheless, consumer-oriented firms with higher information asymmetry are more likely to adopt Twitter. We also find that B2C companies are significantly more likely and quicker to adopt Twitter than B2B firms and that B2C firms with higher information asymmetry are even more likely to adopt Twitter than other firms. Such a finding is consistent with the perspective that consumer-oriented firms have more to gain from engaging customers through social media (Lee et al. 2015, Tang 2018).  We also find that litigation risk is an influential factor on Twitter adoption, but the concerns about proprietary costs are unlikely to influence Twitter adoptions.

Finally, this study does not examine the economic consequences of adopting Twitter. That a firm spends resources to administer Twitter and increases its usage over time implies that firms find Twitter beneficial to the firm. As a result, s study demonstrating the value relevance of Twitter usage is a fruitful area of future research.

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## Appendix A

### Variables Description

| | |
|---|---|
| Advertising_Expense | Advertising expenses divided by total assets of the firm at the end of the preceding quarter |
| Analyst_Following | Natural Log of one plus number of analysts following (from IBES database) at the end of the preceding quarter |
| BTM | Ratio of book value of equity and market value of equity to at the end of the preceding quarter |
| BidAskSprd | Difference between daily ask and bid prices scaled by the daily closing share price averaged during the preceding quarter. |
| B2C | 1 if the firm is engaged in business-to-consumer operations, and 0 otherwise. |
| Both | 1 if the firm is engaged in both business-to-consumer and business-to-business operations, and 0 otherwise |
| Cash | Cash and short-term investments scaled by total assets at the end of the preceding quarter |
| Firm_Age | Natural log of number of years listed on Compustat |
| Firm_Press_Release | Natural Log of one plus the number of press releases issued by the firm and distributed via a news provider during the preceding quarter (Lexis-Nexis). |
| Firm_Size | Natural log of the firm's total assets at the end of the preceding quarter |
| HHI | Herfindahl-Hirschman Index =$\sum$(ith firm's sales/SIC 2-digit industry sales)$^2$ |
| Inst_Ownership | Number of shares held by institutional investors scaled by total shares outstanding as of the preceding quarter end date (this variable is from Thomson Reuters 13-f ; variable name instown_perc) |
| Intangibles | Intangible assets divided by total assets of the firm at the end of the preceding quarter (Compustat INTANQ ) |
| Leverage | Sum of long-term debt and debt in current liabilities scaled by total assets the firm at the end of the preceding quarter |
| Litigation | 1 if the firm's primary industry has a high incidence of past litigation as categorized by Francis et al. (1994) (four-digit SIC codes for high litigation risk firms are:2833–2836 and 8731–8734 (biotechnology);3570–3577 and 7370–7374 (computers); 3600–3674 (electronics and 5200–5961 (retailing)), and 0 otherwise |
| Media_Following | Natural Log of one plus the number of news articles written about a firm during the preceding quarter (Lexis-Nexis). |

| | |
|---|---|
| Num_Shareholders | Natural Log of one plus number of shareholders (in millions) at the end of the preceding quarter |
| ROA | Quarterly Income before Extraordinary items summed over the predicting four quarters divided by average total assets during the preceding four quarters. |
| RD_Expense | R&D expenses divided by total assets of the firm at the end of the preceding quarter |
| Retail | 1 if the firm reports Compustat SIC codes 5200-5999, and 0 otherwise |
| Ret_Volatility | Standard deviation of stock returns over the prior 250 days, where at least 100 days of stock returns are required for inclusion in the sample |
| Silicon | 1 if the firm is headquartered in Silicon Valley, and 0 otherwise |

**Figure 1A: Time trend of new firms adopting Twitter**

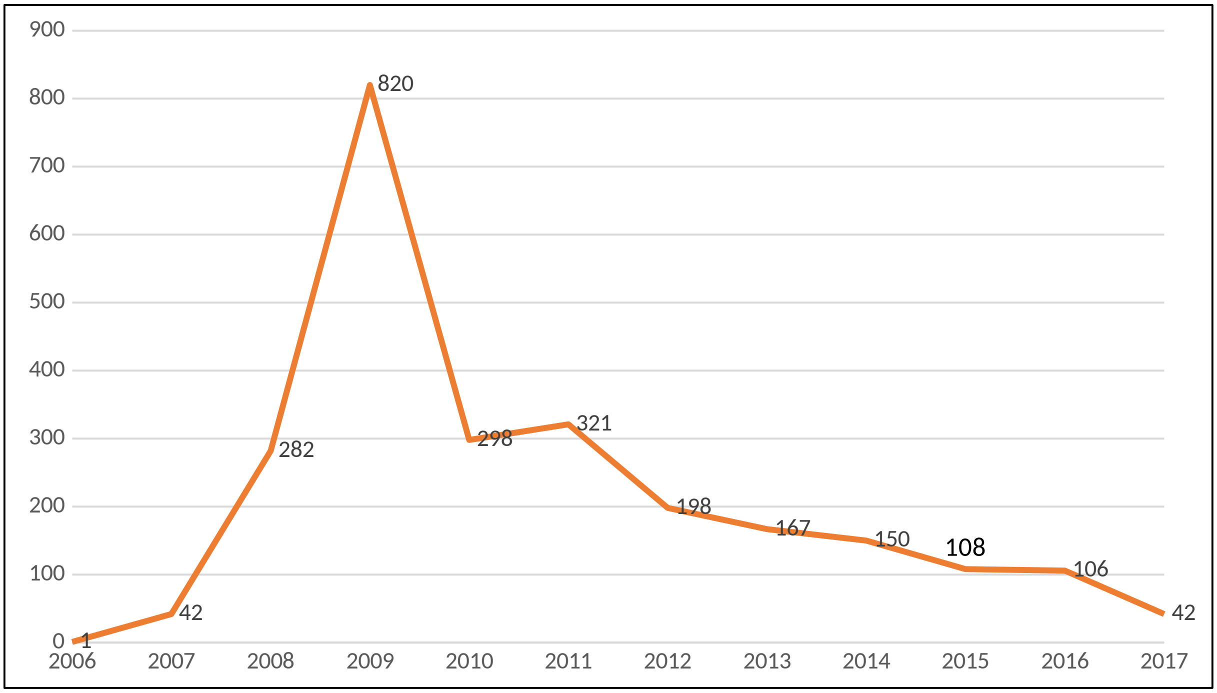


Figure 1A shows the year wise trend of new firms creating Twitter accounts

**Figure 1B: Cumulative proportion of firms on Twitter, delineated by S&P 1500 and non-S&P 1500 firms**

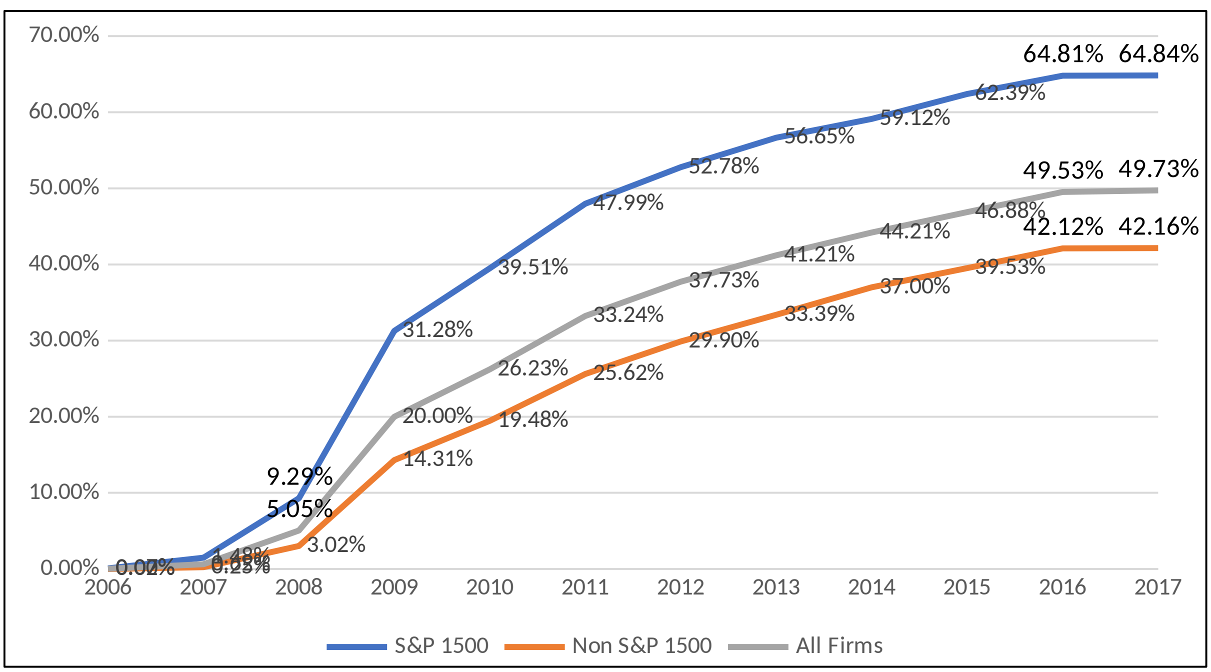

Figure 1B shows the proportion of firms than have a Twitter account delineated by S&P 1500, non-S&P 1500, and all firms.

**Figure 1C: Time trend of average Tweets per firm**

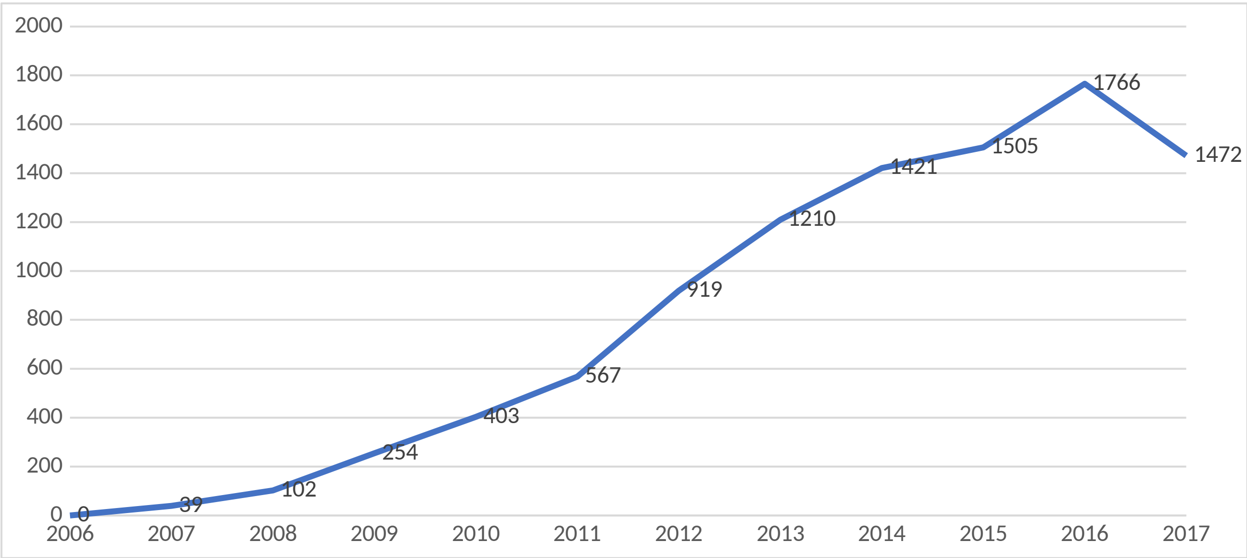


Figure 1C shows the year wise trend of average tweets made by all Twitter firms

**Figure 1D Time trend of total Tweets by firms**

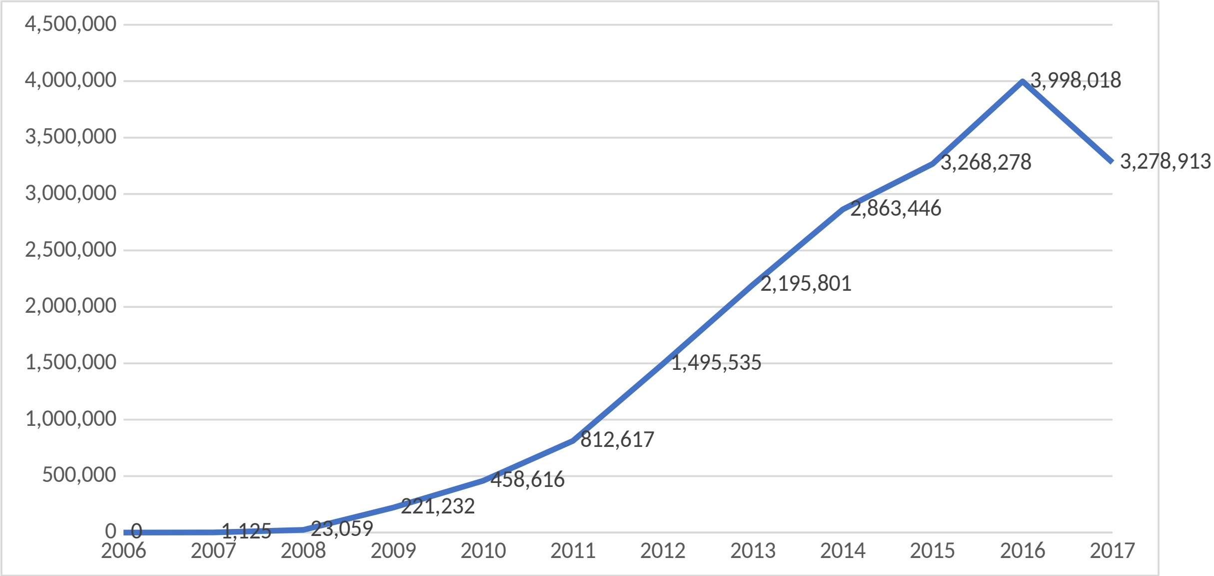


Figure 1D shows the year-wise trend of total tweets made by all Twitter firms

**Table 1A:**
Top 10 of the Fama French -48 industries with the highest percentage of Twitter firm-quarters (Twitter=1) between 2006 to 2017.

| Industry | | Number of Firm -Quarters | | |
|---|---|---|---|---|
| Fama-French Industry Code | Industry Name | Total | Twitter | % Twitter Firm Quarters |
| 42 | Retail | 7,366 | 3,791 | 51.47% |
| 34 | Business Services | 21,056 | 9,659 | 45.87% |
| 35 | Computers | 5,146 | 2,344 | 45.55% |
| 43 | Restaurants, Hotels, Motels | 2,963 | 1,286 | 43.40% |
| 3 | Candy & Soda | 656 | 278 | 42.38% |
| 10 | Apparel | 1,878 | 776 | 41.32% |
| 6 | Recreation | 936 | 376 | 40.17% |
| 4 | Beer & Liquor | 542 | 201 | 37.08% |
| 9 | Consumer Goods | 1,837 | 676 | 36.80% |
| 36 | Electronic Equipment | 10,529 | 3,808 | 36.17% |

**Table 1B:**
Top 10 of the Fama French -48 industries with the lowest percentage of Twitter firm-quarters (Twitter=1) between 2006 to 2017.

| Industry | | Number of Firm -Quarters | | |
|---|---|---|---|---|
| Fama-French Industry Code | Industry Name | Total | Twitter | % Twitter Firm Quarters |
| 26 | Defense | 348 | 67 | 19.25% |
| 11 | Healthcare | 3,104 | 557 | 17.94% |
| 7 | Entertainment | 2,289 | 403 | 17.61% |
| 16 | Textiles | 363 | 63 | 17.36% |
| 19 | Steel Works | 1,636 | 281 | 17.18% |
| 28 | Non-Metallic and Industrial Metal mining | 1,320 | 211 | 15.98% |
| 25 | Shipbuilding, Railroad Equipment | 434 | 69 | 15.90% |
| 47 | Trading | 14,807 | 2,252 | 15.21% |
| 48 | Almost Nothing | 2,244 | 319 | 14.22% |
| 30 | Petroleum and Natural Gas | 7,655 | 1,006 | 13.14% |

**Table 2: Descriptive Statistics of Twitter and Non-Twitter Firm Quarters**

| | Twitter Firm-Quarters | | Non-Twitter Firm-Quarters | | t-test of Difference (Twitter – Non_Twitter) | |
|---|---|---|---|---|---|---|
| **Variable** | **# Obs** | **Mean** | **# Obs** | **Mean** | **Diff** | **t-stat** |
| Advertising_Expense | 37,252 | 0.014 | 78,176 | 0.010 | 0.005 | 25.93*** |
| Analyst_Following (raw) | 37,252 | 10.576 | 78,176 | 6.760 | 3.816 | 82.55*** |
| Analyst_Following(In Log) | 37,252 | 2.096 | 78,176 | 1.627 | 0.469 | 76.01*** |
| BTM | 37,252 | 0.500 | 78,176 | 0.586 | -0.085 | -26.55*** |
| BidAskSprd | 37,252 | 0.003 | 78,176 | 0.006 | -0.003 | -46.13*** |
| B2C | 37,252 | 0.127 | 78,176 | 0.082 | 0.045 | 24.50*** |
| Both | 37,252 | 0.550 | 78,176 | 0.518 | 0.032 | 10.30*** |
| Cash | 37,252 | 0.207 | 78,176 | 0.221 | -0.014 | -9.17*** |
| Firm_Age | 37,252 | 23.997 | 78,176 | 20.416 | 3.581 | 42.21*** |
| Firm_Press_Releases (raw) | 37,252 | 12.132 | 78,176 | 2.408 | 9.724 | 45.61*** |
| Firm_Press_Releases(In Log) | 37,252 | 1.296 | 78,176 | 0.423 | 0.873 | 130.000*** |
| Firm_Size | 37,252 | 12038.900 | 78,176 | 4465.961 | 7572.939 | 49.79*** |
| HHI | 37,252 | 0.085 | 78,176 | 0.082 | 0.004 | 7.46*** |
| Inst_ Ownership | 37,252 | 0.612 | 78,176 | 0.586 | 0.026 | 14.21*** |
| Intangibles | 37,252 | 0.203 | 78,176 | 0.167 | 0.036 | 28.11*** |
| Leverage | 37,252 | 0.204 | 78,176 | 0.207 | -0.003 | -2.38** |
| Litigation | 37,252 | 0.415 | 78,176 | 0.302 | 0.113 | 38.32*** |
| Media_Following(In Numbers) | 37,252 | 67.589 | 78,176 | 25.876 | 41.712 | 26.56*** |
| Media_Following(In Log) | 37,252 | 1.872 | 78,176 | 1.291 | 0.581 | 59.55*** |
| Num_Shareholders | 37,252 | -6.691 | 78,176 | -7.020 | 0.329 | 23.07*** |
| ROA(Annual) | 37,252 | -0.001 | 78,176 | -0.007 | 0.006 | 18.79*** |
| RD_Expense | 37,252 | 0.014 | 78,176 | 0.016 | -0.003 | -10.81*** |
| Retail | 37,252 | 0.102 | 78,176 | 0.047 | 0.055 | 35.67*** |
| Ret_Volatility | 37,252 | 0.027 | 78,176 | 0.033 | -0.005 | -48.62*** |
| Silicon | 37,252 | 0.109 | 78,176 | 0.075 | 0.033 | 19.01*** |

See Appendix A for variable definitions. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

**Table 3: Covariate Correlations (All correlations are significant at one percent or better unless p-values are stated otherwise: ($p<0.05$, $p<0.10$, NS=$p>0.10$)**

| Pearson Correlation | Twitter | Adv. Expense | Analyst Following | BTM | BidAsk Sprd | B2C | BOTH | Cash | Firm Age | Firm_Press Releases | Firm Size |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Advertising_Expense | 0.050 | 1 | | | | | | | | | |
| Analyst_Following | 0.171 | 0.039 | 1 | | | | | | | | |
| BTM | -0.071 | -0.115 | -0.177 | 1 | | | | | | | |
| BidAskSprd | -0.094 | 0.017 | -0.402 | 0.233 | 1 | | | | | | |
| B2C | 0.065 | 0.328 | 0.093 | -0.033 | -0.025 | 1 | | | | | |
| Both | 0.022 | -0.005$^{NS}$ | -0.108 | 0.005$^{NS}$ | 0.004$^{NS}$ | -0.367 | 1 | | | | |
| Cash | 0.042 | 0.083 | -0.054 | -0.156 | 0.088 | -0.095 | 0.132 | 1 | | | |
| Firm_Age | 0.129 | -0.093 | 0.032 | 0.020 | -0.099 | -0.043 | -0.053 | -0.260 | 1 | | |
| Firm_Press_Release | 0.365 | 0.003$^{NS}$ | 0.178 | -0.108 | -0.145 | 0.018 | 0.002$^{NS}$ | -0.042 | 0.193 | 1 | |
| Firm_Size | 0.143 | -0.070 | 0.289 | 0.113 | -0.098 | -0.049 | 0.120 | -0.113 | 0.230 | 0.157 | 1 |
| HHI | 0.012 | 0.011 | 0.086 | 0.040 | -0.019 | 0.293 | 0.012 | -0.183 | -0.147 | -0.240 | -0.135 |
| Inst_ Ownership | -0.131 | 0.001$^{NS}$ | 0.255 | -0.028 | -0.259 | 0.038 | -0.028 | 0.003$^{NS}$ | -0.172 | -0.004$^{NS}$ | 0.051 |
| Intangibles | 0.037 | 0.000$^{NS}$ | 0.075 | -0.106 | -0.058 | -0.057 | 0.055 | -0.222 | -0.077 | 0.078 | -0.072 |
| Leverage | -0.008$^{0.10}$ | -0.026 | 0.075 | -0.152 | -0.035 | 0.038 | -0.007$^{NS}$ | -0.330 | 0.115 | 0.096 | 0.039 |
| Litigation | 0.132 | 0.108 | 0.074 | -0.116 | 0.038 | 0.339 | -0.037 | 0.348 | -0.185 | 0.193 | 0.230 |
| Media_Following | 0.150 | 0.065 | 0.376 | -0.080 | -0.178 | 0.133 | -0.015 | -0.151 | 0.266 | 0.239 | 0.424 |
| Num_Shareholders | 0.063 | -0.039 | 0.224 | -0.006 | -0.114 | 0.029 | -0.024 | -0.258 | 0.430 | 0.193 | 0.230 |
| ROA | 0.020 | 0.099 | 0.160 | -0.276 | -0.313 | 0.081 | -0.017 | -0.046 | 0.019 | 0.019 | -0.015 |
| R&D expense | 0.028 | -0.041 | -0.014 | -0.136 | 0.116 | -0.144 | 0.072 | 0.510 | -0.147 | -0.006 | -0.101 |
| Retail | 0.096 | 0.286 | 0.104 | 0.037 | -0.023 | 0.841 | -0.309 | -0.078 | -0.049 | 0.017 | -0.043 |
| Ret_Volatility | -0.135 | 0.038 | -0.226 | 0.257 | 0.408 | -0.004$^{NS}$ | 0.028 | 0.145 | -0.232 | -0.250 | -0.133 |
| Silicon | 0.055 | 0.007$^{NS}$ | 0.071 | -0.045 | 0.021 | -0.063 | 0.049 | 0.301 | -0.108 | 0.013 | -0.011 |

| Pearson Correlation | HHI | Inst_ Ownership | Intangibles | Leverage | Litigation | Media Following | NumShare holders | ROA | R&D expense | Retail | Ret Volatility |
|---|---|---|---|---|---|---|---|---|---|---|---|
| HHI | 1 | | | | | | | | | | |
| Inst_ Ownership | 0.018 | 1 | | | | | | | | | |
| Intangibles | -0.143 | 0.063 | 1 | | | | | | | | |
| Leverage | 0.047 | -0.001$^{NS}$ | 0.205 | 1 | | | | | | | |
| Litigation | -0.070 | 0.033 | 0.009$^{0.10}$ | -0.159 | 1 | | | | | | |
| Media_Following | 0.111 | 0.002$^{NS}$ | 0.034 | 0.126 | -0.025 | 1 | | | | | |
| Num_Shareholders | 0.071 | -0.089 | -0.027 | 0.114 | -0.119 | 0.395 | 1 | | | | |
| ROA | 0.034 | 0.132 | 0.036 | -0.124 | 0.003$^{NS}$ | 0.107 | 0.057 | 1 | | | |
| RD_Expense | -0.226 | -0.030 | -0.034 | -0.184 | 0.360 | -0.132 | -0.171 | -0.274 | 1 | | |
| Retail | 0.339 | 0.040 | -0.126 | 0.011 | 0.459 | 0.121 | 0.036 | 0.081 | -0.129 | 1 | |
| Ret_Volatility | 0.025 | -0.022 | -0.135 | 0.006$^{NS}$ | 0.066 | -0.163 | -0.203 | -0.361 | 0.134 | 0.013 | 1 |
| Silicon | -0.110 | 0.004$^{NS}$ | -0.006$^{NS}$ | -0.132 | 0.224 | -0.028 | -0.107 | -0.058 | 0.326 | -0.049 | 0.034 |

**Table 4**

**Duration model estimates for the propensity of firms having a Twitter account**

Full sample: 2006-2017

| VARIABLES | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Constant | -40.445 | -40.455 | -40.419 | -40.444 | -40.482 |
| | (-0.005) | (-0.005) | (-0.005) | (-0.005) | (-0.005) |
| HHI | -0.103 | -0.107 | -0.075 | -0.087 | -0.119 |
| | (-1.351) | (-1.376) | (-0.976) | (-1.114) | (-1.533) |
| Litigation | 0.259*** | 0.260*** | 0.264*** | 0.261*** | 0.253*** |
| | (16.491) | (15.572) | (16.771) | (15.609) | (14.929) |
| BTM | -0.188*** | -0.179*** | -0.188*** | -0.181*** | -0.180*** |
| | (-13.507) | (-12.858) | (-13.522) | (-13.012) | (-12.947) |
| Silicon | 0.040** | 0.042** | 0.037** | 0.041** | 0.042** |
| | (2.194) | (2.306) | (2.009) | (2.22) | (2.309) |
| Intangibles | 0.041 | 0.035 | 0.037 | 0.034 | 0.036 |
| | (1.32) | (1.124) | (1.199) | (1.09) | (1.169) |
| Ret_Volatility | 2.435*** | 2.145*** | 2.345*** | 2.039*** | 2.158*** |
| | (4.767) | (4.184) | (4.589) | (3.97) | (4.207) |
| Firm_Size | 0.065*** | 0.071*** | 0.063*** | 0.070*** | 0.070*** |
| | (12.432) | (13.637) | (12.165) | (13.332) | (13.361) |
| Media_Following | 0.088*** | 0.085*** | 0.090*** | 0.086*** | 0.085*** |
| | (20.931) | (20.122) | (21.244) | (20.329) | (20.092) |
| Analyst_Following | 0.119*** | 0.111*** | 0.119*** | 0.112*** | 0.112*** |
| | (12.238) | (11.424) | (12.304) | (11.552) | (11.509) |
| Inst_Ownership | 0.004 | 0.000 | 0.005 | 0.001 | 0.004 |
| | (0.139) | (0.011) | (0.181) | (0.034) | (0.136) |
| Num_Shareholders | -0.002 | -0.002 | -0.002 | -0.002 | -0.002 |
| | (-0.714) | (-0.666) | (-0.556) | (-0.555) | (-0.725) |
| Firm_Press_Release | 0.002 | 0.003 | 0.001 | 0.003 | 0.003 |
| | (0.294) | (0.498) | (0.181) | (0.455) | (0.531) |
| BidAskSprd | -4.292*** | -4.138*** | -10.921*** | -5.276*** | -4.120*** |
| | (-3.951) | (-3.811) | (-6.892) | (-4.738) | (-3.794) |
| Both | 0.052*** | | 0.023 | | 0.037*** |
| | (3.963) | | (1.562) | | (2.787) |
| B2C | 0.153*** | | 0.084*** | | 0.045 |
| | (5.893) | | (3.063) | | (1.231) |
| Advertising_Expense | | 1.699*** | | 1.659*** | 1.628*** |
| | | (9.747) | | (9.5) | (9.17) |
| Retail | | 0.140*** | | 0.100** | 0.110** |
| | | (3.538) | | (2.469) | (2.062) |
| Both* BidAskSprd | | | 7.993*** | | |

| | | | | | |
|---|---|---|---|---|---|
| | | | (4.716) | | |
| B2C* BidAskSprd | | | 19.589*** | | |
| | | | (7.798) | | |
| Retail* BidAskSprd | | | | 15.066*** | |
| | | | | (5.744) | |
| Firm_Age | -0.018*** | -0.018*** | -0.018*** | -0.018*** | -0.017*** |
| | (-33.810) | (-33.970) | (-33.829) | (-34.037) | (-33.579) |
| Cash | 0.097*** | 0.084** | 0.095** | 0.084** | 0.081** |
| | (2.642) | (2.272) | (2.572) | (2.264) | (2.179) |
| Leverage | -0.578*** | -0.562*** | -0.579*** | -0.565*** | -0.565*** |
| | (-18.819) | (-18.36) | (-18.846) | (-18.43) | (-18.423) |
| ROA | -2.494*** | -2.582*** | -2.503*** | -2.608*** | -2.580*** |
| | (-15.500) | (-16.014) | (-15.552) | (-16.152) | (-16.008) |
| RD_Expense | -1.545*** | -1.544*** | -1.477*** | -1.536*** | -1.503*** |
| | (-6.173) | (-6.186) | (-5.895) | (-6.149) | (-6.016) |
| Observations | 115,428 | 115,428 | 115,428 | 115,428 | 115,428 |
| Year-quarter Fixed effects | Yes | Yes | Yes | Yes | Yes |
| Fama-French 10 Fixed effects | Yes | Yes | Yes | Yes | Yes |
| AIC | 13892.6 | 13815.2 | 13836.3 | 13787.9 | 13811.1 |
| Log likelihood | -6908 | -6870 | -6878 | -6855 | -6866 |
| LR chi2 | 53167 | 53244 | 53227 | 53274 | 53252 |
| *p* | 10.34 | 10.35 | 10.34 | 10.35 | 10.35 |

z-statistics in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Estimates are based on the duration analysis using a Weibull distribution without frailty, modeling a firm's presence on Twitter for a sample of all firm-quarters from 2006 to 2017 (both Twitter and non-Twitter firm- quarters). All variables are as defined in Appendix A.

**Table 5**

**Duration model estimates for the propensity of firms having a Twitter account**

Early Adoption sample: 2006-2011

| VARIABLES | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Constant | -62.479 | -61.602 | -61.934 | -61.597 | -61.777 |
| | (-0.005) | (-0.008) | (-0.007) | (-0.008) | (-0.008) |
| HHI | 0.080 | 0.078 | 0.129 | 0.112 | -0.017 |
| | (0.494) | (0.48) | (0.801) | (0.687) | (-0.105) |
| Litigation | 0.244*** | 0.242*** | 0.255*** | 0.242*** | 0.205*** |
| | (7.949) | (7.406) | (8.273) | (7.404) | (6.132) |
| BTM | -0.196*** | -0.180*** | -0.198*** | -0.182*** | -0.187*** |
| | (-7.787) | (-7.142) | (-7.893) | (-7.241) | (-7.424) |
| Silicon | 0.033 | 0.029 | 0.017 | 0.022 | 0.040 |
| | (0.900) | (0.787) | (0.469) | (0.611) | (1.112) |
| Intangibles | 0.789 | 0.359 | 0.439 | 0.125 | 0.159 |
| | (0.884) | (0.401) | (0.490) | (0.139) | (0.178) |
| Ret_Volatility | -0.148** | -0.161** | -0.157** | -0.166** | -0.183*** |
| | (-2.274) | (-2.473) | (-2.405) | (-2.54) | (-2.804) |
| Firm_Size | 0.070*** | 0.092*** | 0.066*** | 0.090*** | 0.087*** |
| | (6.374) | (8.393) | (6.056) | (8.135) | (7.885) |
| Media_Following | 0.151*** | 0.141*** | 0.155*** | 0.143*** | 0.140*** |
| | (17.166) | (15.948) | (17.537) | (16.119) | (15.873) |
| Analyst_Following | 0.087*** | 0.066*** | 0.085*** | 0.067*** | 0.066*** |
| | (4.227) | (3.167) | (4.100) | (3.231) | (3.194) |
| Inst_Ownership | 0.103* | 0.080 | 0.114** | 0.085 | 0.103* |
| | (1.781) | (1.403) | (1.977) | (1.478) | (1.79) |
| Num_Shareholders | 0.026*** | 0.024*** | 0.026*** | 0.024*** | 0.024*** |
| | (4.291) | (4.025) | (4.389) | (4.099) | (4.000) |
| Firm_Press_Release | 0.006 | 0.010 | 0.007 | 0.010 | 0.011 |
| | (0.362) | (0.579) | (0.421) | (0.601) | (0.666) |
| BidAskSprd | -9.463*** | -9.469*** | -26.211*** | -11.606*** | -9.296*** |
| | (-4.713) | (-4.719) | (-7.831) | (-5.56) | (-4.629) |
| Both | 0.247*** | | 0.170*** | | 0.208*** |
| | (9.024) | | (5.625) | | (7.550) |
| B2C | 0.558*** | | 0.400*** | | 0.162** |
| | (11.067) | | (7.420) | | (2.191) |
| Advertising_Expense | | 4.064*** | | 3.930*** | 3.780*** |
| | | (12.543) | | (12.048) | (11.323) |
| Retail | | 0.596*** | | 0.530*** | 0.527*** |
| | | (7.463) | | (6.517) | (4.942) |
| Both* BidAskSprd | | | 19.536*** | | |
| | | | (5.584) | | |

| | | | | | |
|---|---|---|---|---|---|
| B2C* BidAskSprd | | | 36.513*** | | |
| | | | (8.477) | | |
| Retail* BidAskSprd | | | | 20.773*** | |
| | | | | (5.056) | |
| Firm_Age | -0.014*** | -0.015*** | -0.014*** | -0.015*** | -0.014*** |
| | (-13.75) | (-14.621) | (-13.812) | (-14.644) | (-13.829) |
| Cash | 0.033 | 0.029 | 0.038 | 0.033 | -0.024 |
| | (0.434) | (0.371) | (0.496) | (0.424) | (-0.307) |
| Leverage | -0.572*** | -0.556*** | -0.571*** | -0.561*** | -0.576*** |
| | (-8.778) | (-8.529) | (-8.748) | (-8.586) | (-8.83) |
| ROA | -3.093*** | -3.119*** | -3.132*** | -3.163*** | -3.226*** |
| | (-9.155) | (-9.212) | (-9.244) | (-9.331) | (-9.521) |
| RD_Expense | -3.164*** | -2.973*** | -2.913*** | -2.932*** | -2.852*** |
| | (-5.062) | (-4.784) | (-4.655) | (-4.714) | (-4.602) |
| Observations | 62,136 | 62,136 | 62,136 | 62,136 | 62,136 |
| Year-quarter Fixed effects | Yes | Yes | Yes | Yes | Yes |
| Fama-French 10 Fixed effects | Yes | Yes | Yes | Yes | Yes |
| AIC | -6836.0 | -6915.5 | -6903.2 | -6935.5 | -6969.7 |
| Log likelihood | 3453 | 3495 | 3490 | 3506 | 3524 |
| LR chi2 | 20829 | 20913 | 20903 | 20935 | 20971 |
| *p* | 22.21 | 22.17 | 22.22 | 22.19 | 22.21 |

z-statistics in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Estimates are based on the duration analysis using a Weibull distribution without frailty, modeling a firm's presence on Twitter for a sample of early-adopters of Twitter between 2006 to 2011 (both Twitter and non-Twitter firm- quarters). All variables are as defined in Appendix A.

**Table 6**

**OLS model estimates for volume of Tweets:**
**Dependent Variable = Log (1+ Tweets)**

Twitter full sample: 2006-2017

| VARIABLES | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Constant | -1.485** | -1.622** | -1.767** | -1.530** | -1.591** |
| | (-2.037) | (-2.083) | (-2.294) | (-2.109) | (-2.057) |
| HHI | 0.436 | 0.127 | -0.137 | 0.473 | 0.172 |
| | (0.743) | (0.216) | (-0.232) | (0.808) | (0.294) |
| Litigation | 0.618*** | 0.571*** | 0.487*** | 0.623*** | 0.574*** |
| | (6.004) | (5.445) | (4.548) | (6.053) | (5.471) |
| BTM | -0.386*** | -0.308*** | -0.328*** | -0.389*** | -0.316*** |
| | (-4.005) | (-3.301) | (-3.516) | (-4.058) | (-3.426) |
| Silicon | 0.241* | 0.278** | 0.269** | 0.239* | 0.275** |
| | (1.777) | (2.062) | (1.994) | (1.763) | (2.04) |
| Intangibles | 0.108 | 0.226 | 0.222 | 0.114 | 0.227 |
| | (0.503) | (1.031) | (1.016) | (0.532) | (1.036) |
| Ret_Volatility | -1.215 | -2.622 | -3.461 | -1.255 | -2.876 |
| | (-0.431) | (-0.949) | (-1.268) | (-0.444) | (-1.041) |
| Firm_Size | 0.056 | 0.122*** | 0.106*** | 0.057 | 0.120*** |
| | (1.405) | (3.065) | (2.708) | (1.407) | (3.014) |
| Media_Following | 0.213*** | 0.180*** | 0.182*** | 0.213*** | 0.181*** |
| | (6.433) | (5.376) | (5.563) | (6.426) | (5.406) |
| Analyst_Following | 0.143** | 0.082 | 0.09 | 0.142** | 0.083 |
| | (2.121) | (1.256) | (1.375) | (2.119) | (1.264) |
| Inst_Ownership | -0.018 | 0.008 | 0.029 | -0.011 | 0.011 |
| | (-0.087) | (0.041) | (0.149) | (-0.057) | (0.055) |
| Num_Shareholders | 0.045** | 0.040* | 0.040* | 0.045** | 0.040* |
| | (2.062) | (1.841) | (1.861) | (2.053) | (1.868) |
| Firm_Press_Release | 0.034 | 0.038 | 0.04 | 0.033 | 0.037 |
| | (1.171) | (1.329) | (1.433) | (1.165) | (1.29) |
| BidAskSprd | 1.736 | 5.23 | 5.349 | 9.084 | 3.055 |
| | (0.275) | (0.848) | (0.863) | (1.001) | (0.473) |
| Both | 0.408*** | | 0.339*** | 0.453*** | |
| | (4.419) | | (3.723) | (4.512) | |
| B2C | 0.803*** | | -0.528** | 0.770*** | |
| | (4.759) | | (-2.259) | (4.261) | |
| Advertising_Expense | | 11.722*** | 11.560*** | | 11.677*** |
| | | (8.728) | (8.588) | | (8.701) |
| Retail | | 0.558*** | 1.369*** | | 0.476** |
| | | (2.856) | (4.582) | | (2.295) |
| Both* BidAskSprd | | | | -14.157 | |

| | | | | | |
|---|---|---|---|---|---|
| | | | | (-1.359) | |
| B2C* BidAskSprd | | | | 9.193 | |
| | | | | (0.555) | |
| Retail* BidAskSprd | | | | | 27.354 |
| | | | | | (1.633) |
| Firm_Age | -0.011*** | -0.011*** | -0.010*** | -0.011*** | -0.011*** |
| | (-3.01) | (-3.172) | (-2.887) | (-2.999) | (-3.189) |
| Cash | 0.115 | 0.254 | 0.178 | 0.125 | 0.254 |
| | (0.47) | (1.052) | (0.746) | (0.512) | (1.056) |
| Leverage | -0.469** | -0.371* | -0.339 | -0.478** | -0.377* |
| | (-2.074) | (-1.652) | (-1.527) | (-2.121) | (-1.678) |
| ROA | 2.654*** | 2.287** | 1.960** | 2.663*** | 2.242** |
| | (2.815) | (2.504) | (2.14) | (2.832) | (2.455) |
| RD_Expense | -5.854*** | -5.310*** | -4.867*** | -5.931*** | -5.291*** |
| | (-4.399) | (-4.046) | (-3.739) | (-4.462) | (-4.036) |
| Observations | 37,252 | 37,252 | 37,252 | 37,252 | 37,252 |
| R-squared | 0.189 | 0.211 | 0.218 | 0.19 | 0.212 |
| Year-quarter Fixed effects | Yes | Yes | Yes | Yes | Yes |
| Clustering of Errors | Firm | Firm | Firm | Firm | Firm |

t-statistics in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Estimates are based on the OLS estimation, modeling the firm's volume of tweets (log(1+tweets)) between 2006 to 2017. The sample addresses only the firms that have a Twitter account. All variables are as defined in Appendix A.