Do(n't) Believe Everything you Hear About Disclosure

– Twitter and the Voluntary Disclosure Effect

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Abstract

This study reveals a positive relationship between disclosure through Tweets and institutional ownership, especially after the maximum number of characters per Tweet is doubled. Additionally, changes in institutional ownership are more pronounced for higher levels of Twitter disclosure, suggesting that investors are more sensitive to disclosure changes in more transparent information environments. As managers tend to avoid disclosure of negative news through fast-paced Twitter and at the same time make use of Twitter's dynamic nature to disseminate positive news as quickly as possible, the effect on institutional ownership is more pronounced for positive Tweets, contrary to other disclosure channels. Finally, for high (low) increases (decreases) of Twitter disclosure measured as the frequency of Tweets, a change in Twitter disclosure is associated with a stronger reaction of institutional ownership.

1. Introduction

Even before Elon Musk's infamous Tweet about private funding for Tesla on August 7, 2018 and the subsequent legal ramifications (Wattles, 2019), Tweets and Twitter use have shown to have undeniable implications for the stock market. The Tweets of Donald Trump had such far-reaching impact on the stock market that JP Morgan created the "Volfefe Index" to quantify the relationship between his Tweets and volatility in the stock market (Horowitz, 2019).

But not all investors are equally susceptible to Twitter use, and not all investors are equally important to executives. Institutional investors have historically held the majority of stock (e.g., Gompers & Metrick, 2001). Furthermore, they have been shown to have beneficial effects on management and the firm, such as taking short-term pressure off managers (e.g., Bushee, 1998; Wahal & McConnell, 2000). This leaves more resources for long-term oriented goals such as R&D (e.g., Bushee, 1998) or investments in property, plant and equipment (Wahal & McConnell, 2000). Additionally, institutional investors strengthen corporate governance (e.g., English, Smyth, & McNeil, 2004), even though this effect is not undisputed (e.g., Chen, Harford, & Li, 2007). An improvement in corporate governance might not be welcomed by management in the first instance but is well-received by shareholders and thus benefits the firm overall.

Thus, it is sensible for a firm to aim to attract institutional investors. One of the main ways to increase institutional holdings in the firm is by increasing disclosure (Bushee & Noe, 2000), as above all large institutional investors are more likely to invest in firms with higher levels of disclosure (Diamond & Verrecchia, 1991). In part, this attraction of institutional investors to firms with more disclosure results from the lower information asymmetry and the lower risk associated with investing in such firms (El-Gazzar, 1998).

In this context, voluntary disclosure is of special interest, as mandatory disclosure is codified and enforced and thus does not differ largely across similar firms. Commonly discussed forms of voluntary disclosure are traditional management forecasts (e.g., Aboody & Kasznik, 2000; Frankel, McNichols, & Wilson, 1995; Skinner, 1994), conference calls (e.g., Brown, Hillegeist, & Lo, 2004; Hollander, Pronk, & Roelofsen, 2010), conference presentations (e.g., Bushee, Jung, & Miller, 2011), investor days (e.g., Kirk & Markov, 2016), or roadshows (e.g., Bushee, Gerakos, & Lee, 2018). One of the most recent additions to the growing list of disclosure channels is disclosure through social media and especially Twitter (e.g., Blankespoor, Miller, & White, 2014; Jung, Naughton, Tahoun, & Wang, 2018; Lei, Li, & Luo, 2018; Tang, 2018; Yang, Liu, & Zhou, 2016). While Twitter has been shown to be perceived as a source of information dissemination and disclosure by investors (Blankespoor, Miller, & White, 2014), no literature has considered its impact on institutional investors in particular.

By examining the relationship between Twitter disclosure and institutional ownership, this study attempts to close this gap in the literature. First, a positive relationship between Twitter use and institutional ownership is hypothesized and tested. Second, as managers might seek to postpone or delay negative disclosure (Pae, 2005), especially through Twitter as a fast-moving disclosure channel, they will likely reduce the number of negative Tweets or delay them until the information surprise of their content is insignificant. Thus, the reaction of institutional investors to positive Tweets should be larger than their reaction to negative Tweets. This results in the second hypothesis that disclosure of positive information through Twitter is associated with more institutional ownership than disclosure of negative information through Twitter. Third, the impacts of increases and decreases of Twitter use on institutional ownership are also considered.

This study contributes to the literature in three important ways. First, the study closes a gap in the literature that has not considered institutional investors as the recipients of disclosure through social media specifically, even though institutional investors might deviate largely from retail investors (e.g., El-Gazzar, 1998; Smith, 1996). In this regard, the tests show that a strong positive relationship exists between Twitter use and institutional ownership, regardless of the valence of disclosure. However, a difference-in-difference analysis reveals that this relationship is mainly true after Twitter doubled its character limit per Tweet. While Twitter has been an information dissemination channel before the character limit increase (e.g., Blankespoor, Miller, & White, 2014), it has been mainly used to disseminate non-mainstream news (Zhao, Jiang, Weng, He, Lim, Yan, & Li, 2011). Thus, a potential explanation is that the doubling of character limit per Tweet has drawn media attention to Twitter as a disclosure medium and has established Twitter as a respectable and trustworthy disclosure channel among institutional investors. While it appears to be intuitive that an increase in the maximum character limit relates to increases in disclosure level, industry reports show that the average actual Tweet length has not significantly increased (e.g., Perez, 2018).

Second, contrary to other forms of disclosure, positive valence in Twitter disclosure has generally a larger impact on institutional ownership than negative valence. Because managers are reluctant to disclose bad news (e.g., Pae, 2005; Skinner, 1994), especially through the relatively fast-paced disclosure channel Twitter, information disclosed through negative Tweets is likely less new as it might have broken from other sources. Thus, the impact on institutional ownership is insignificant. As positive news is disclosed in a timelier manner to make use of the dynamic nature of Twitter, the novelty of information is likely greater, resulting in a positive and significant effect on institutional ownership.

Finally, propensity score matching analyses indicate that generally, large increases and small decreases of Twitter disclosure levels are followed by stronger reactions of institutional investors. This result emphasizes the importance of Twitter disclosure for the overall information environment of a firm. However, this result was not confirmed for the levels of institutional ownership. Hence, the third hypothesis that an increase (decrease) in Twitter disclosure leads to an increase (decrease) of institutional ownership, is only partially supported.

The rest of the paper is structured as follows. The next section develops the hypotheses. Section 3 describes the sample and data. Section 4 presents the results and section 5 concludes.

2. Hypotheses Development and Related Literature

2.1 Literature on Institutional Ownership

Ever since the 1970s, institutional investors have collectively held the largest portion of all shares in the stock market (e.g., Gompers & Metrick, 2001; Hessel, 1981; Jones, 1972; Li, Moshirian, Pham, & Zein, 2006; Hunnicutt, 2017). Since only a relatively small number of investors have to be approached to sell a relatively large number of shares, wooing institutional investors is an efficient strategy for firms. Besides the sheer holding size, institutional ownership is also associated with a number of benefits for firms, such as increased shareholder wealth (Lee & Park, 2009).[1] The most-researched and potentially largest benefit of institutional investors

[1] We do not distinguish between committed and transient institutional investors in this study. Long-term oriented committed institutional investors have been shown to have a positive impact on firms by for example strengthening corporate governance and limiting managerial misbehaviors (Harford, Kecskes, & Mansi, 2018). While short-term oriented transient institutional investors generally appear to have a negative impact on firm outcomes (e.g., Bushee, 1998; Kahn & Winton, 1998), other research shows that transient institutional investors can make a positive difference. For example, firms with higher transient institutional ownership have more incentives to avoid negative earnings surprises and are as a result more likely to meet or beat analyst forecasts (Matsumoto, 2002). Additionally, short-term institutional investor trades by themselves work as a disciplinary mechanism to keep managers in check (Gallagher, Gardner, & Swan, 2013).

comes from their active monitoring role (Agrawal & Mandelker, 1990; Del Guercio, Seery, & Woidtke, 2008; Gillian & Starks, 2000; Gordon & Pound, 1993; Kim, Miller, Wan, & Wang, 2016). Institutional investors closely monitor the firms they have invested in and take action for the benefit of the firm. In fact, institutional investors are the largest activists, especially for US stocks (Becht, Franks, Grant, & Wagner, 2017), due to their larger stake in the firm relative to the stake of retail investors (Aggarwal, Saffi, & Sturgess, 2015).

The increased shareholder activism has positive consequences for the firm. As Smith (1996) shows, for firms that adopt changes suggested by activist shareholders, shareholder wealth increases. For firms that choose not to accept the suggested changes, shareholder wealth decreases. Apart from this direct effect, institutional ownership has an indirect effect on a number of beneficial outcomes for the firm, potentially through increased monitoring. For example, institutional ownership leads to more conservative accounting (Ramalingegowda & Yu, 2012), decreases accrual-based earnings management (Chung, Firth, & Kim, 2002; Kim et al., 2016) and increases the pay-for-performance sensitivity of executive compensation (Hartzell & Starks, 2003).[2]

Another important benefit of institutional ownership is that it alleviates the pressure on managers for short-term results (e.g., Bushee, 1998; Wahal & McConnell, 2000). In case of an unsuccessful short-term project, managers do not have to fear for their job. This allows managers to focus on the long-term profitability of the firm and undertake for example more R&D to that end. R&D activity and innovation have been shown to be an increasing function of both domestic

[2] Institutional investors have been associated with a short-term increase in discipline in the firm, resulting from simply buying stocks (English, Smyth, & McNeil, 2004). However, more recent findings have shown that the so-called "CalPERS effect" appears to no longer exist (Chen, Harford, & Li, 2007).

and international institutional ownership (Aghion, Van Reenen, & Zingales 2013; Bena, Ferreira, Matos, & Pires, 2017; Bushee, 1998; Hu, Jo, Wang, & Xie, 2018; Luong, Moshirian, Nguyen, Tian, & Zhang, 2017). Managers also invest more in property, plant, and equipment with increasing levels of institutional ownership. Similar to R&D, the increase in tangible assets might hurt short-term profitability, but potentially increases long-term performance (Wahal & McConnell, 2000).

2.2 Literature on Disclosure and Hypotheses Development

Because of the various benefits of institutional ownership for firms outlined above, it is in the best interest for firms to attract institutional investors. This can be done in a variety of ways such as aiming to receive favorable recommendations from rating agencies (Bhattacharya, Wei, & Xia, 2019), or having strong corporate governance in place (Chung & Zhang, 2011; Froot & Teo, 2008; Li et al., 2006). An increase in disclosure does play a major role in attracting institutional investors in general (Bushee & Noe, 2000). Especially large investors are attracted by increased levels of voluntary disclosure and the resulting decreased information asymmetry (Diamond & Verrecchia, 1991). Similar to an increase in advertising, which draws institutional and retail investors alike (Grullon, Kanatas, & Weston, 2004), higher levels of disclosure grab the attention of institutional shareholders and thus lead to more institutional investors (Bushee & Noe, 2000). Institutional investors are drawn toward higher levels of disclosure, as they are conservative investors. Increased disclosure allows them to make a more informed investment decision about the firm. While this is generally desirable, institutional investors are legally required to be more prudent in their investing (El-Gazzar, 1998).

Disclosure is a broad field of study and has been widely researched. Of specific interest is voluntary disclosure. As mandatory disclosure is required by law, it can be assumed to be approximately equal for all firms. The abundance of available venues for disclosure with varying levels of selectiveness led to the passage of Regulation Fair Disclosure (Reg. FD) in 2014. It states that any disclosure has to be made accessible to all investors in a fair and complete manner (SEC, 2014).

Even voluntary disclosure compliant with Reg. FD can take many forms. Historically, much research focused on management forecasts (e.g., Aboody & Kasznik 2000; Frankel, McNichols, & Wilson, 1995; Skinner, 1994). More recently, other forms of disclosure have attracted more scholarly attention. Among these are conference calls (e.g., Brown, Hillegeist, & Lo, 2004; Hollander, Pronk, & Roelofsen, 2010), conference presentations (e.g., Bushee, Jung, & Miller, 2011), investor days (e.g., Kirk & Markov, 2016)), or roadshows (e.g., Bushee, Gerakos, & Lee, 2018). Other relatively new areas of research make use of electronic resources to analyze disclosure. For example, Lang and Stice-Lawrence (2015) use textual analysis of annual reports to examine the results of transparency. In a similar vein, Ertugrul, Lei, Qiu, and Wan (2017) show that electronic 10-K filings with a larger file size, and 10-K filings with a larger portion of weak or uncertain modal words face stricter loan terms and a heightened stock crash risk in the future.

Social media analysis combines the two fields, as it is both the most recent stream of the disclosure literature and requires electronic tools to analyze. Overall, the most commonly considered form of social media is Twitter (e.g., Blankespoor, Miller, & White, 2014; Jung et al., 2018; Lei, Li, & Luo, 2018; Tang, 2018; Yang, Liu, & Zhou, 2016), although single studies also consider other social media like Facebook (e.g., Danbolt, Siganos, & Vagenas-Nanos, 2015) or Weibo (e.g., Feng & Johansson, 2019). The results show that Twitter is generally seen as a regular form of disclosure by investors. For example, Blankespoor, Miller, and White (2014) show that firm news dissemination via Twitter decreases the overall information asymmetry, measured by a lower bid-ask spread and greater abnormal depths. This effect is stronger for firms which would be less visible otherwise, consistent with the finding that Twitter disseminates non-mainstream news (Zhao et al, 2011). Moreover, the collective opinion from Tweets before earnings announcements allows to accurately predict earnings surprises. Again, this effect is stronger for firms in otherwise weaker information environments (Bartov, Faurel, & Mohanram, 2018)[3].

Since institutional investors are more conservative investors, they are attracted to less risky investments. Firms in more transparent information environments, for example through more disclosure, constitute less risky investments. As Twitter is considered a direct disclosure tool, higher Twitter use should hence attract more institutional investors. This leads to the first hypothesis:

HYPOTHESIS 1: *Firms with a higher frequency of Twitter use have higher institutional ownership.*

Similar to other disclosure media, managers might attempt to forego disclosure of negative news altogether, especially for temporary surprises (Kasznik & Lev, 1995), citing for example large costs (Pae, 2005; Skinner, 1994). Furthermore, Tweets are more spontaneous than SEC filings or conference calls, because the latter are scripted to a large degree (Brown, Call, Clement, & Sharp, 2019). Since even managers with a reputation for being honest cheat and shirk (Dejong,

[3] In this study, propensity score matching analyses reveal that for firms in otherwise high- and low-information environments, no significant difference exists for the attraction of institutional investors through Twitter disclosure.

Forsythe, & Lundholm, 1985), managers might shy away from getting caught up in their spur-of-the-moment Tweets later, especially since management weighs the benefits and risks before taking on any voluntary disclosure (Evans III & Sridhar, 2002; Wagenhofer, 1990). Additionally, the valence of Tweets likely affects the consequences of the disclosure, similar to other disclosure channels (Skinner, 1994). Twitter is likely used less to disseminate bad news, as Tweets with bad news are associated with more negative articles written about the firm in traditional media (Jung et al., 2018).

As managers generally prefer to postpone the disclosure of negative news (Kasznik & Lev, 1995), they prefer to avoid disclosure of negative news through the fast-paced medium Twitter.[4] As they postpone disclosure, negative news disclosed on Twitter have likely been leaked or disclosed through other, less dynamic channels. Thus, the information content of negative Twitter disclosure is likely small, as is the reaction of investors. For positive disclosure, the opposite effect is expected. Firms make use of the fast-paced nature of Tweets to disclose positive information as quickly as possible. Thus, more Tweets have positive valence and the subsequent reaction to positive Tweets is larger, due to the novelty of the information disclosed. This argument sets Twitter apart from more traditional, less dynamic disclosure channels in which disclosure of negative information conveys more information (e.g., Skinner, 1994). Thus, the second hypothesis is:

[4] Even if Twitter is assumed to be disseminated to all market participants equally fast as, for example, SEC filings, the character restrictions make interpreting the bite-sized information contained in Tweets easier for human readers and algorithms.

HYPOTHESIS 2: *Firms with disclosure through Tweets with positive information have higher institutional ownership than firms with disclosure through Tweets with negative information.*

Similar to advertising (Grullon, Kanatas, & Weston, 2004), Twitter use should draw the attention of investors and thus increase institutional ownership. If an increase in institutional ownership is driven by the voluntary disclosure associated with Tweets, an increase in Twitter use by the firm should be followed by an increase in institutional ownership. Thus, the third hypothesis is:

HYPOTHESIS 3: *An increase (decrease) in Twitter use leads to an increase (decrease) in institutional ownership.*

3. Data and Sample

3.1 Sample Construction

The sample period spans the years from 2015 to 2018 as data on the Twitter variables are only available after 2014. Only firms in the S&P 1500 are considered to eliminate the discontinuity effect of index listing on institutional ownership and voluntary disclosure recorded in previous literature (e.g., Bird & Karolyi, 2016; Chen, Dong, & Lin, 2019; Crane, Michenaud, & Westen, 2016; Khan, Srinivasan, & Tan, 2017; Lin, Mao, & Wang, 2018; Schoenfeld, 2017). Despite being in the S&P 1500, the company Twitter is excluded from all analyses to avoid distorting influences. The inherent proficiency, as well as the increased motivation to further promote Tweets as a disclosure channel differentiate the company from all other companies.

Prior literature has examined relationships between Tweets and the stock market with daily data (e.g., Blankespoor, Miller, & White, 2014; Ge, Kurov, & Wolfe, 2018). Since long-term effects are the scope of this, and because not all variables (e.g., *CEOequity*, *CEOstkcomp*, and *sprank*) are available on a daily or monthly basis, all data are aggregated to the firm-quarter level of analysis. For the same reason, it is difficult to anticipate how long it takes for the Twitter use of a firm to show effect. However, as weekly data on institutional ownership in a firm are available[5], it appears reasonable to assume that institutional investors react to changes in Twitter use of a firm within a quarter. The final sample consists of 6516 firm-quarter observations with complete data.

3.2 Measures of Institutional Ownership

Data on institutional ownership, shares outstanding, Twitter use, disclosure, and corporate governance are obtained through the Bloomberg Terminal. The institutional ownership of a firm is measured by the number of shares outstanding held by institutional investors, divided by the total number of shares outstanding, *linstcsho*. The change in institutional ownership, *instcshochng*, is the change in institutional ownership between the current and the previous quarters. As previous literature has shown, higher institutional ownership leads to more disclosure in the future (Boone & White, 2015; El-Gazzar, 1998). Thus, institutional ownership of the last period, *laglinstcsho*, has to be controlled for in all regressions.

As found by Anderson and Lee (1997), and confirmed by other research (e.g., Dass, Nanda, & Xiao, 2017; Hribar, 2016), the data source can alter the results of analyses, especially in the context of ownership studies. These studies find that the highest-quality data are obtained from

[5] See, for example, the variable EQY_INST_PCT_SH_OUT on the Bloomberg Terminal.

firm publications such as SEC filings directly. The data available through the Bloomberg Terminal are obtained not only from 13F filings, but also from US and International Mutual Funds, Schedule Ds for US insurance firms, and aggregated institutional stake holdings. Thus, Bloomberg offers a very comprehensive data source. However, by including all data sources, certain shares are included more than one time, leading to institutional holdings of more than 100% for some companies. As it is impossible to know which shares are counted multiple times and which are not, a correction is necessary. Thus, the log is taken of all institutional ownership variables. This correction affects all observations in a comparable way, which is appropriate as the multiple-counting problem also affects all observations equally. From an econometric stance, taking the log of all institutional ownership variables preserves the variance in the sample, leading to overall robust coefficient estimates.[6]

Additionally, the method to collect data from a variety of SEC filings is the method of choice for Bloomberg. Bloomberg is the industry leader in the financial data industry with about 325,000 users and a market share of around 33.3% (Finextra Research, 2018; Wallstreetprep.com, 2020). Thus, it is the most commonly used financial data tool, not only by academic researchers but also practitioners. Consequently, in following the approach of Bloomberg and using their data, the results are likely most relevant for practitioners as well. Additionally, given the high cost of a subscription to Bloomberg, if the data were economically different from actual data in a significant

[6] An easy way to counter this problem would be to exclude firm-quarter observations with more than 100% institutional holdings. However, this would not only truncate the data, but also not solve the problem of multiple-counted institutional ownership for firms with less than a 100% stake. Regardless, when we exclude all firm-quarter observations with more than 100% institutional ownership, the results remain the same.

way, users can reasonably be assumed to use other financial data providers instead. As Bloomberg is the market leader, its data appear to approximate the "true" underlying data best.[7]

3.3 Measures of Twitter Disclosure

For the Twitter variables, all Twitter accounts of a firm are considered. We measure the total number of Tweets as the sum of the number of positive, negative, and neutral Tweets. The log of the total number of Tweets and the log of each type of Twitter disclosure variable (positive, negative, or neutral) are used in the analyses as the range for each variable is relatively large. To determine both the overall valence of a Tweet and which sentiment value a Tweet receives, Bloomberg uses supervised machine-learning that specializes on financial language. Each Tweet receives a value in the range of [-1;1]. In addition to its technological sophistication, this method is appropriate to detect sentiment in Tweets, as Kouloumpis, Wilson and Moore (2011) conclude that n-grams and lexicographic features produce the best results with the highest reliability. The Twitter disclosure and sentiment measures, along with all other variables, are defined in detail in the appendix.

3.4 Measures of Other Disclosure

Botosan and Plumlee (2002) claim that omitting any form of disclosure might result in an omitted variable bias and hence incorrect inferences. Thus, other forms of disclosure, such as management forecasts in SEC filings (Aboody & Kasznik, 2000; Skinner, 1994), conference calls (Brown, Hillegeist, & Lo, 2004, conference presentations (Bushee, Jung, & Miller, 2011), or

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[7] However, as shown below, the results are robust to using other measures of institutional ownership.

investor days (Kirk & Markov, 2016) are controlled for as well. The data on disclosure through SEC filings for the variable *comsec*, disclosure through press releases, *compress*, and other disclosure, *comother*, are all frequency counts. Press releases describe media coverage of the firm, not press releases by the firm, as defined by Bloomberg. They are included as a control variable, as they are generally instigated by the firm in some way. Additionally, media coverage increases the information dissemination and as such is an important disclosure tool (Fang & Peress, 2009).

3.5 Measures of Corporate Governance

Voluntary disclosure is also a positive function of the portion of outside directors on the board (Cheng & Courtenay, 2006). In fact, institutional shareholders are generally encouraged by strong corporate governance to invest in a firm (Chung & Zhang, 2011; Froot & Teo, 2008; Li et al., 2006). Corporate governance is proxied by the Institutional Shareholder Service (ISS) Quality Score (Chung & Zhang, 2011).[8] The Quality Score enters the regressions as the variable *issq*.

One of the most important drivers of voluntary disclosure identified in the literature is the portion of stock compensation in the compensation package of the CEO. It is expected to be positively related to voluntary disclosure, because more strategic disclosure translates to more favorable conditions to execute the options (Aboody & Kasznik, 2000; Brockman, Martin, & Puckett, 2010; Cheng & Lo, 2006; Nagar, Nanda, & Wysocki, 2003; Noe, 1999). Since more favorable stock prices also benefit CEOs with higher levels of ownership in selling some of their

[8] The quality score contains several corporate governance provisions, including outside directors or voting methods, which have, in isolation, been the subject of previous research as well (e.g., Cheng & Courtenay, 2006; Chung & Lee, 2020; Lim, Matolcsy, & Chow, 2007). A detailed list and explanation of the different corporate governance provisions can be found in Chung and Zhang (2011). Downgrades in the ISS Quality Score have been shown to be associated with significant negative abnormal returns (Guest & Nerino, 2019). Thus, the data is comparable to other corporate governance measures.

shares (Brockman, Khurana, & Martin, 2008), levels of stock ownership are also controlled for. Moreover, CEO compensation is also negatively related to institutional ownership (e.g., Hartzell & Starks, 2003). Data on the equity stake of the CEO, *CEOequity* and the portion of stock compensation in the overall compensation package of the CEO, *CEOstkcomp*, are taken from ExecuComp. As CEOs have also been shown to increase disclosure in their last year before exiting (Cassell, Huang, & Sanchez, 2013), a dummy variable (*CEOleave*) indicates over the last four quarters that the current year is the last year of the CEO. The departure date of a CEO is obtained from Audit Analytics.

3.6 Measures of Firm Characteristics

In the aftermath of disclosure-related lawsuits, firms decrease their disclosure (Rogers & Van Buskirk, 2009). Thus, another dummy variable, *lawsuit,* indicates a disclosure-related lawsuit in the previous quarter. Lawsuit data stem from the Stanford Law School Securities Class Action Clearinghouse database. Data for the other control variables are taken from the annual and quarterly files of Compustat. *leverage* measures the total debt of a firm and is calculated by the sum of long-term and short-term debt, scaled by total assets, as prior literature has shown a negative relationship between disclosure and debt (Eng & Mak, 2003) and between institutional ownership and debt (Pushner, 1995). *adex* is the advertising expenditures of a firm. Advertising expenditures are controlled for because investors are drawn towards firms with more advertising (Grullon, Kanatas, & Weston, 2004). Since data on advertising expenditures are only available on an annual basis, they are assumed to be equally distributed over the year and divided by four. If no data were available, advertising expenditures were assumed to be non-trivial in accordance with disclosure laws (Mizik & Nissim, 2011) and set to zero. Additionally, disclosure is more likely to occur for larger firms (Chow & Wong-Boren, 1987; Eng & Mak, 2003). Hence, *size* measures the firm size and is calculated by taking the log of total assets.[9] Since growth firms were among the first to incorporate conference calls in their disclosure portfolio (Frankel, Johnson, & Skinner, 1999), *mb*, the market-to-book ratio, is included in the analyses as well. To avoid multicollinearity issues with the total debt measure, it is calculated as the market value of equity divided by total assets.[10]

If no quarterly data are available, *leverage*, *size*, *mb*, and *mkshr* are assumed to be constant over one year and missing quarterly data are replaced with yearly data for that specific firm. Young firms use more disclosure to signal their economic viability (Wasley & Wu, 2006). The firm age is controlled for with the variable *age*, which is calculated by subtracting the year and quarter of the initial public offering from the current year and quarter. If no IPO date was available through Compustat, the year and quarter of the firm's first appearance on Compustat is subtracted from the current year and quarter. Finally, since especially small institutional investors follow rating agencies over other credit signs such as analysts (Bhattacharya et al., 2019), *sprank* measures the credit rating, based on the Standard & Poor's rating. As the S&P rating is alphabetical but clearly ordinal, it is converted to numerical values.[11]

In more concentrated industries, the overall disclosure level is smaller because of associated proprietary costs (Ali, Klasa, & Yeoung, 2014). Industry concentration is proxied with the market share (*mkshr*), which is measured as the sales of a firm divided by the total sales of all

[9] For multicollinearity reasons, it was not possible to use the log of total sales or the market capitalization, as proposed as alternative measures by previous literature (Dang, Li, & Yang, 2018).
[10] This modified calculation is not expected to alter the results. The market-to-book ratio does not impact institutional ownership, as institutional investors do not bet on classic predictors of stock return, such as market-to-book ratio, momentum, or accruals (Lewellen, 2011).
[11] For example, A as the highest rating obtains the value 7, B obtains the value of 6, and so on. If a firm did not receive a credit rating, *sprank* is set to 0.

firms in the same 4-digit GICS industry.[12] In order to avoid multicollinearity with the industry concentration measure, no controlling for whether a firm operates in a business-to-consumer (B2C) market was possible. Firms in B2C markets are expected to be more likely to disclose (Arya & Mittendorf, 2013). Thus, this effect is picked up by industry-fixed effects, which are included in all regressions. Finally, year-fixed effects enter all but the difference-in-difference analyses and the propensity score matching.

4. Empirical Results

4.1 Main Analyses

4.1.1 Basic Statistics

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insert Table 1 about here

Table 1 shows the descriptive statistics. In order to avoid the distorting effect of outliers, all variables except the Twitter valence measures, *issq*, *lawsuit*, *CEOleave,* and *sprank* are winsorized at the 2% and 98% level.[13] Table 1 also shows the raw values for institutional ownership (*instcsho)*, the lagged value of institutional ownership (*laginstcsho)*, and the Twitter disclosure levels of all Tweets (*twitcnt*), positive Tweets (*twitcntpos*), negative Tweets (*twitcntneg*), and neutral Tweets (*twitcntntr*). These variables are not considered in any of the analyses but convey a more intuitive picture of the sample. Additionally, the raw values reveal that

[12] The GICS industry classification is chosen because it provides a better approximation of actual industries than for example the SIC or NAICS classification system (Bhojraj, Lee, & Oler, 2003).
[13] *lawsuit* and *ceolave* are dummy variables and thus can only take values of either 0 or 1. The Twitter valence measures take values of between positive and negative 1. *issq* can take any value from 0 to 10, and *sprank* takes values from 0 to 7. Thus, these variables are already standardized, and it would hurt the analyses to winsorize them as well.

positive Tweets are 11.67% more frequent in the mean and 12.57% more common in the median.[14] This is in line with the argument for Hypothesis 2 that firms are more likely to use Twitter to disclose positive instead of negative news.

On average, institutional ownership in the S&P 1500 was approximately 69% over the sample period and declined by 6% per quarter. While there is a large variation in the raw data for all Twitter disclosure levels, the winsorized and log-variables appear not to be distorted by outliers to a large degree. Overall, Tweets appear to be more positive than negative, which is also supported by the maximum Twitter valence being more positive than the minimum Twitter valence being negative in both the mean and the median. As the S&P 1500 firm list gets updated frequently, it is biased towards successful firms. However, in terms of market-to-book ratio or firm size, the sample does not show any large biases, as both the mean and the median appear comparable in size to other corporate finance studies (Dang, Li, & Yang, 2018).

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insert Table 2 about here

Table 2 shows the Pearson correlation coefficients for the variables of interest. Both the measure of change in institutional ownership and the measure of institutional ownership are highly significantly correlated with the Twitter disclosure level variables. Additionally, the change in institutional ownership is significantly correlated with extremely positive or extremely negative Tweets, but not with the average valence of Tweets. The same is true for the level of institutional

[14] The relative frequencies are calculated by subtracting the mean (median) of negative Tweets from the mean (median) of positive Tweets and dividing the difference by the mean (median) of the total number of Tweets. For example, the 11.672% increase is calculated as (280.180 – 198.603) / 698.870 = 0.11672.

ownership, *linstcsho*, except for extremely negative Tweets, which are not significantly correlated with institutional ownership.

4.1.2 Regression Models

For all regression analyses, OLS regressions are used. The general regression equation is

$$linstcsho_{i,j} \text{ or } instcshochng_{i,j} = \beta_0 + \beta_1 ltwitcnt_{i,j} + \beta_2 laglinstcsho_{i,j} + \beta_3 comother_{i,j} + \beta_4 comsec_{i,j} + \beta_5 compress_{i,j} + \beta_6 issq_{i,j} + \beta_7 CEOequity_{i,j} + \beta_8 CEOstkcomp_{i,j} + \beta_9 adex_{i,j} + \beta_{10} leverage_{i,j} + \beta_{11} size_{i,j} + \beta_{12} mb_{i,j} + \beta_{13} age_{i,j} + \beta_{14} mkshr_{i,j} + \beta_{15} lawsuit_{i,j} + \beta_{16} CEOleave_{i,j} + \beta_{17} sprank_{i,j} + \varepsilon \quad (1),$$

where all variables are defined earlier, and the indices stand for the *i*th firm in the *j*th quarter. The regressions are conducted on the firm-quarter level, controlling for year-[15] and industry-fixed effects. *ltwitcnt* stands for the main independent variable of interest and changes over the different regression specifications.

4.1.3 The Effect of Twitter Disclosure on Institutional Ownership

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insert Table 3 about here

Table 3 shows the results of OLS regressions of the levels of institutional ownership on Twitter disclosure in Panel A and the changes in institutional ownership on Twitter disclosure in Panel B. An increase in Twitter disclosure by 1% leads to an increase of institutional ownership

[15] We also re-run our all analyses with quarter-fixed effects and get virtually the same results.

of about 0.005% to 0.010%[16], as all columns of Panel A show. These changes appear to be small at first glance. However, an increase in Twitter disclosure by 1% (which translates to about 7 Tweets per quarter) leads to institutional investors purchasing stock with an average value of about $10,883 to $21,800, according to the results. Across all models, all Twitter disclosure levels are highly significant, even after controlling for alternative forms of disclosure. Additionally, disclosure through SEC filings (*comsec*) are significant predictors of institutional ownership. Previous institutional ownership is also highly significant.

The results from the models in Panel B reveal that the changes to institutional ownership are stronger for higher levels of Twitter disclosure, but only slightly so. This is potentially due to the circumstance that both an increase and a decrease in Twitter disclosure are easier to observe for already-high levels of Twitter disclosure. All Twitter disclosure measures are again highly significant after controlling for other disclosure forms, and remain the only significant among all disclosure measures across all models of changes in institutional ownership. Like in Panel A, previous levels of institutional ownership are a highly significant predictor. As the changes are calculated based on the lagged levels of institutional ownership, this result is not surprising.

The percentage of stock compensation carries a negative sign in all models of Panel A, and a positive sign in all models of Panel B. Thus, the percentage of stock compensation is negatively related to the levels, and positively related to the changes in institutional ownership. These results are in line with previous literature (e.g., Hartzell & Starks, 2003). While the results for governance,

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[16] Since both the dependent and the main independent variable are log-transformed and the unit of the dependent variable is percentage, percentage changes in institutional ownership are calculated as 100*e^(log([100+1]/100)*coefficient estimate). For example, the calculation of the percentage change in institutional ownership of one percentage change in Twitter disclosure in model (1) is calculated as 100*e^(log([100+1]/100)*0.020) = 0.009.

firm size, growth, and age point in the direction of previous literature as outlined above, the results for leverage oppose previous findings. According to Pushner (1995), leverage is negatively related to institutional ownership. However, for the levels of institutional ownership in Panel A, leverage is positively significant at the 10% level. As institutional investors take short-term pressures off managers (e.g., Aghion et al., 2013), they are in a better position to issue debt. Since long-term growth can become more of a goal than short-term flexibility, debt might become a more attractive alternative. However, due to the low level of significance, this relationship is likely not a main aspect of institutional ownership. For the changes in institutional ownership shown in Panel B, *leverage* is insignificant. Taken together, the results of Table 3 support Hypothesis 1, which states that firms with a higher frequency of Twitter use have higher institutional ownership.

4.1.4 Difference-in-Difference Regressions of Levels and Changes in Institutional Ownership on Twitter Variables

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insert Table 4 about here

Table 4 shows the results of means difference *t*-tests comparing institutional ownership and the change in institutional ownership in the week before an exogenous shock to Twitter disclosure to the week after that event.[17] The exogenous shock to the Twitter disclosure level stems from Twitter doubling the character limit of a Tweet from 140 to 280 characters on November 7,

[17] Using a daily time-horizon is not possible, as the data on institutional ownership on the Bloomberg Terminal get updated only once a week. When considering the quarter before and after the maximum character increase (consistent with the empirical setting), a significant difference in the change in institutional ownership exists. The changes in institutional ownership are significantly smaller after the maximum character increase. The level of institutional ownership is still not significantly different, analogue to the week-level comparisons.

2017 (Larson, 2017). As the results in Table 4 show, the levels of institutional ownership do not significantly differ before and after the event. This result is in line with industry reports, which state that the possibility of longer Tweets did not actually lead to significantly longer Tweets (Perez, 2018). Additionally, changes in institutional ownership are not significantly larger or smaller from changes in institutional ownership before the increase of the character limit per Tweet.

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insert Table 5 about here

Table 5 shows the results of difference-in-difference regressions to account for any omitted variables common to firms of all Twitter disclosure levels. The exogenous shock stems from the doubling of the character limit per Tweet, as for Table 4. However, as data on most of the variables are only available on a quarterly basis, the fiscal quarter before the character limit increase is compared to the fiscal quarter after. Since year-fixed or quarter-fixed effects cannot be included in the analyses due to multicollinearity, only the quarters directly before and after the character limit increase enter the regressions. The quarters in which the character limit increase took place are excluded, because the specific point in time during the quarter is different for different firms, as not all firms end their fiscal quarter in the same month. Additionally, since the character limit increase took effect on November 7, it is not possible to include a subset of firms that end their fiscal year in either October or November. The difference-in-difference variable is the interaction between the event quarter dummy, *eventqtr*, and the respective Twitter disclosure level measures. For example, in Model (1), *eventqtr* is interacted with the Twitter disclosure variable, *ltwitcnt*, to create the difference-in-difference variable *DiDcnt*.

In Panel A, the coefficient estimates of Twitter disclosure are significantly negative. In other words, higher levels of Twitter disclosure are related to lower levels of institutional ownership, contrary to the findings in Table 3. Additionally, the character limit increase also has a negative impact on institutional ownership, as can be seen from the negative sign of *eventqtr*. However, given that this finding conflicts with the results in Table 4, it is likely that an omitted variable is present that changes both the sign and the significance of the difference in institutional ownership from the weekly to the quarterly level of analysis.[18] If both the exogenous shock and the different levels of Twitter disclosure are taken together in the difference-in-difference variable, however, the overall effect is positive. Thus, after the character limit increase, a higher level of Twitter disclosure of all types leads to an increase in institutional ownership.

The results for Panel B, which shows the changes in institutional ownership as the dependent variable, are only partially the same. Neither the Twitter disclosure level (e.g., *ltwitcnt*) nor the character limit increase (*eventqtr*) have a significant impact on the changes in institutional ownership. However, the sign of the insignificant coefficient estimates points in the same directions as in Panel A. Analogue to the models for the levels of institutional ownership, the difference-in-difference estimator is significant and positive. Only for negative Twitter disclosure (*DiDneg*), the effect of Twitter disclosure on the changes in institutional ownership is insignificant. Given the large body of research that finds stronger effects for the disclosure of negative news (e.g., Kasznik & Lev, 1995; Skinner, 1994), this result is highly interesting.

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[18] Untabulated event studies with event windows of [-1;1] and [-2;2] and an estimation window of [-120;-6] only produce insignificant results. Since event studies are designed to detect surprises or abrupt changes, this is not surprising. As Twitter announced their maximum character increase well in advance, the increase was not a surprise. Thus, the event study seems to indicate that firms did not change their Twitter disclosure at once after the maximum character increase, but did so gradually.

Overall, past levels of institutional ownership are again highly significant predictors of both current levels and changes in institutional ownership. Beyond these relationships, only firm size is a significant predictor of the level of institutional ownership in Panel A. The positive sign is in line with previous literature (Chow & Wong-Boren, 1987; Eng & Mak, 2003). For the changes in institutional ownership in Panel B, disclosure through SEC filings is a significantly positive predictor. While this is not an explicit result from previous literature (e.g., Aboody & Kasznik, 2000), it certainly is in line with previous research. Similarly, if the current CEO has less than one year remaining in the firm, the magnitude of changes in institutional ownership is increased. Since previous literature considered the positive effect on disclosure (Cassell, Huang, & Sanchez, 2013), an increase in changes in institutional ownership is a non-surprising extension.

Overall, the results of Table 5 limit the support of Hypothesis 1 to the time period after the character limit increase. Additionally, the results appear to lend preliminary support to Hypothesis 2, as positive Twitter disclosure is always significant, whereas negative Twitter disclosure is not.

4.1.5 OLS Regressions of Levels and Changes in Institutional Ownership on Twitter Valence Variables

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insert Table 6 about here

This section formally examines Hypothesis 2, the relationship between Tweet valence and institutional ownership. Table 6 shows the results of OLS regressions of levels and changes in institutional ownership on Tweet valence variables.

In Panel A, the average Tweet sentiment (*twsentavg*) has a significantly positive relationship with the level of institutional ownership at the 10% level. The coefficient estimates of positive and negative Tweet sentiment in models (2) and (3) are insignificant, with the coefficient estimates being equal in magnitude with opposing signs. As shown in model (4), the maximum Tweet sentiment of each quarter is highly predictive of institutional ownership at the 1% level, whereas the quarterly minimum Tweet sentiment in model (5) is not significant. Thus, the results show that Twitter disclosure with extremely positive sentiment pays for firms, as it results in more institutional ownership. Extremely negative Twitter disclosure has no effect on institutional ownership. While these findings contradict previous literature (e.g., Kasznik & Lev, 1995; Skinner, 1994), they support Hypothesis 2 that positive information disclosure through Twitter is associated with higher institutional ownership than negative information disclosure through Twitter. Furthermore, these findings show that Twitter disclosure is different from disclosure through traditional channels.

The analysis of the changes in institutional ownership in Panel B confirm the results from the analyses of the levels in Panel A. Contrary to the levels, the average Tweet sentiment in model (1) does not have a significant impact on the changes in institutional ownership. Positive and negative Tweet sentiment in models (2) and (3) significantly affect the change in institutional ownership. On average, the effect of positive and negative Tweet sentiment appears to be comparable in magnitude, but opposite in direction. The maximum of Tweet sentiment is again highly significant, whereas the minimum is not. Thus, a more positive Twitter disclosure leads to a stronger positive reaction of institutional investors. Extremely positive Twitter disclosure will increase the magnitude of changes in institutional ownership whereas extremely negative Twitter disclosure does not affect the magnitude of changes in institutional ownership.

The results of the control variables for both the levels and the changes in institutional ownership are largely similar to the results in Table 3. Taken together, the results from Table 6 indicate that more positive Twitter disclosure attracts institutional investors, while the negative Twitter disclosure does not attract institutional investors. This effect is enhanced because more positive Twitter disclosure also provokes larger changes in institutional ownership. Negative Twitter disclosure has only a small impact on the magnitude of the changes in institutional ownership. The attraction of institutional investors is most visible for the largest positive Tweet sentiment each quarter, both in the levels and changes in institutional ownership. Thus, Hypothesis 2 is supported.

4.1.6 Propensity Score Matching of Different Levels and Changes in Twitter Disclosure

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insert Table 7 about here

Table 7 shows the results of several analyses using propensity score matching. The first column shows the results of comparing firm-quarters with high-level Twitter disclosure to firm-quarters with low-level Twitter disclosure. The highest and the lowest septile of Twitter disclosure are converted into a dummy variable that takes the value of 1 for the highest septile, and 0 for the lowest septile.[19] The propensity score is estimated with probit regressions and is based on only the closest match.

The results of the first column of Table 7 show that there is a significantly positive average treatment effect on the treated (*atet*), both of the levels (*linstcsho*) and the changes (*instcshochng*) of institutional ownership. Thus, within the sample, high-level Twitter disclosure firm-quarters are

[19] Septiles are formed to ensure enough firm-quarters in each subgroup to produce a meaningful number of pairs (n=1849).

associated with significantly higher institutional ownership levels and larger changes in institutional ownership than low-level Twitter disclosure firm-quarters. This result adds support to Hypothesis 1.

The remaining eight columns test different levels of increases and decreases in Twitter disclosure. The comparison is made for each firm-quarter relative to the quarter before of the same firm. Since previous literature has not examined increases or decreases of different types of disclosure, no guidance exists to date. Thus, several factors of the magnitude of increases and decreases are considered. For example, the column *twpub+1.5* matches each firm-quarter in which the total number of Tweets increased by a factor of 1.5 or more, with one firm-quarter in which the total number of Tweets increased by less than the factor 1.5, remained stable, or declined.

Most of these propensity score matchings result in insignificant average treatment effects. Increases or decreases in Twitter disclosure are not associated with a significant change in the levels of institutional ownership (*linstcsho*). On the other hand, an increase in Twitter disclosure by a factor of 2.5 or 3 relative to the previous quarter results in a significant increase in attention of institutional investors by 1.9% and 2.9%, respectively, as the coefficient estimates for *instcshochng* in the columns *twpub+2.5* and *twpub+3* show. A decrease of Twitter disclosure by 50% or 100% is associated with stronger changes in institutional ownership as well. These results are in line with the finding that more disclosure attracts more institutional ownership (Diamond & Verrecchia, 1991), thus lending support to Hypothesis 3. However, since this mechanism is not visible across all magnitudes of increase or decrease of Twitter disclosure, Hypothesis 3 is only partially supported. [20]

[20] The next logical step is to compare firm-quarters in the sample, especially high-level Twitter disclosure firm-quarters, to all other listed, especially low-level Twitter disclosure firm-quarters. This helps to eliminate a potential

Taken together, Table 7 further supports Hypothesis 1 and partially supports Hypothesis 3 by showing that the level of institutional ownership increases with more Twitter disclosure and decreases with less Twitter disclosure. Additionally, the reaction by institutional investors is more pronounced for larger increases of 150% or 200%, or smaller decreases of 50% or 100% in Twitter disclosure levels.

4.2 Additional Analyses

Several additional analyses are conducted to assess the robustness of the main results. First, the overall Twitter publication count, *ltwitcnt*, is based on the sum of positive, neutral, and negative Twitter publication counts. However, not all Tweets are considered important enough to receive a valence rating by Bloomberg. The original variable from Bloomberg that includes all Twitter counts is used as an alternative measure of overall Twitter disclosure. While the results generally hold, they are lower in terms of magnitude of the coefficient estimate and significance.

Second, alternative measures of institutional ownership are used in the following set of robustness tests. First, all analyses are repeated with a rescaled institutional ownership variable. This variable is calculated by dividing all institutional ownership values obtained from Bloomberg by the maximum institutional ownership value across all firm-quarter observations. Second, all analyses are repeated by dropping all observations with more than 100% institutional ownership. The results of both sets of analyses are similar to those from the main analyses.

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sample selection bias, following Maskara & Mullineaux, 2011. However, of the firms not included in the S&P 1500, not a single firm-quarter remained for which complete data was available.

Besides the total number of shares outstanding, Bloomberg also provides data on the total number of shares outstanding that have been authorized, issued, purchased, and are held by investors at the period end date. In other words, Bloomberg provides data on the total number of shares outstanding minus the shares held by the firm itself. Mechanically, the number of shares held by investors is smaller than the total number of shares outstanding. Consequently, the institutional ownership measures based on the number of shares held by investors are a little larger. Thus, while the results do not change in terms of sign or significance, the coefficient estimates are larger for this alternative measure.

Furthermore, Lang and Sul (2014) point out that no good measure of industry concentration exists. Thus, industry concentration is also measured with the Herfindahl-Hirschman Index. The results are generally the same as in the main analyses. The same is true if 4-digit GICS industries are replaced with 6-digit GICS industries. The central takeaway from the additional analyses is that the results of the main analyses are robust to a number of different specifications and alternative measurements.

5. Conclusion

Given the important and largely positive implications of institutional ownership, it is in the best interest of executives to attract more institutional investors. One way to do so is by decreasing information asymmetry through increased disclosure. While Twitter has been established to be a valid disclosure channel (e.g., Blankespoor, Miller, & White, 2014), no previous literature exists to establish a link between Twitter disclosure and institutional ownership.

This study fills the gap by showing that more Twitter disclosure is associated with a higher level of institutional ownership. This is especially true after the increase of the maximum number of characters per Tweet. Since this increase did not lead to significantly longer Tweets (Perez, 2018), an explanation is that the increase and the news coverage that came with it established Twitter fully as a respectable and trustworthy disclosure channel.

The results show that positive disclosure is associated with higher levels and larger changes in institutional ownership, suggesting that positive disclosure contains more information than negative disclosure in contrast to other disclosure channels (e.g., Skinner, 1994). A possible explanation is that executives generally attempt to delay or avoid disclosure of negative news. As Twitter is relatively fast-paced compared to other disclosure channels, executives likely avoid using Twitter to disclose negative news. When negative disclosure makes its way to Twitter eventually, it appears to contain less significantly new information. Positive disclosure through Twitter has larger novelty and consequently stronger implications for institutional ownership.

Additionally, for larger increases or smaller decreases of Twitter disclosure, the changes in institutional ownership are higher. Thus, while institutional investors appreciate a large gain in disclosure, they react strongly if previous levels of disclosure are rolled back even by a little, as institutional investors are conservative investors (El-Gazzar, 1998).

The main limitation of this study is that the data on institutional ownership are possibly biased. While including the data from all SEC filings concerning institutional ownership is the most comprehensive method, double-counting a portion of the shares cannot be avoided. This problem is attenuated by taking the log of all institutional ownership variables, thus reducing the distorting impact of the error. An alternative that has been frequently used in previous studies is the use of only institutional ownership disclosed in 13F filings. As these data omit part of the shares owned by institutional investors, they are biased as well. The more comprehensive data are used, as this method is employed by Bloomberg. Since Bloomberg is mainly used by investors and analysts, the results supposedly are of greater use to these practitioners as well. Additionally, data on press releases from firms were not available. While at least a part of the disclosure is likely contained in the media coverage that was included, the missing disclosure might potentially bias the results. Finally, the study contains only four years of data. Thus, the results might be driven, at least in part, by contemporary effects beyond what could be controlled for with fixed effects.

This study opens up a number of avenues for future research. For example, as Elliott, Grant, and Hodge (2018) report, investors trust the personal Twitter account of CEOs more than the official firm Twitter account or press releases by the firm. Thus, a more differentiated examination of the effect of CEO Tweets on institutional investors would extend the boundaries of both disclosure and institutional ownership research. Additionally, as for all forms of disclosure (e.g., Bhattacharya, Ecker, Olsson, & Schipper, 2012), disclosure quality likely affects the effects of Twitter disclosure as well. Specifically, Tweet readability and accuracy could be examined in this regard.

Finally, while Twitter has been the subject of some previous research (e.g., Blankespoor, Miller, & White, 2014; Ge, Kurov, & Wolfe, 2018; Jung et al., 2018), other social media exist as well (e.g., Danbolt, Siganos, & Vagenas-Nanos, 2015; Drake, Roulstone, & Thornock, 2012). For example, given the large impact of Facebook in the 2016 presidential election (e.g., Mims, 2016), an analysis of the implications of disclosure through Facebook in general, and the impact on institutional investors in particular is warranted.

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Appendix. Variable Definitions

A. Institutional Ownership Measures

instcshochng	change in institutional ownership, measured as the portion of shares outstanding held by institutional investors held at the end of this quarter minus the portion of shares outstanding held by institutional investors at the end of last quarter
linstcsho	institutional ownership, measured as the log of the ratio of shares held by institutional investors to the total number of total shares outstanding
laglinstcsho	past institutional ownership, measured as the lagged value of *linstcsho*

B. Twitter Disclosure and Sentiment Measures

ltwitcnt	Twitter disclosure, measured as the log of the sum of positive, negative, and neutral Tweets
ltwitcntpos	positive Twitter disclosure, measured as the log of the number of positive Tweets
ltwitcntneg	negative Twitter disclosure, measured as the log of the number of negative Tweets
ltwitcntntr	neutral Twitter disclosure, measured as the log of the number of neutral Tweets
twsentavg	Twitter feed sentiment, measured as the average of sentiment scores for all Tweets in a quarter
twsentmin	lowest Twitter feed sentiment, measured as the minimum of sentiment scores for all Tweets in a quarter
twsentmax	highest Twitter feed sentiment, measured as the maximum of sentiment scores for all Tweets in a quarter

C. Control Variables

comsec	SEC-filing disclosure, measured as the number of SEC filings
compress	press release disclosure, measured as the number of press releases
comother	other disclosure, measured as the number of other firm communication (e.g., earnings announcements, conference calls, presentations)
issq	corporate governance, measured with the Institutional Shareholder Service Quality Score (Chung & Zhang, 2011)
CEOequity	equity stake of the CEO, measured as the percentage of stock held by the CEO
CEOstkcomp	portion of stock compensation, measured as the share of stock compensation in the overall compensation package of the CEO
adex	quarterly advertising expenditures
leverage	leverage, measured as the sum of long- and short-term debt divided by total assets
size	firm size, measured as the log of total assets
mb	market-to-book ratio, measured as the market value of equity divided by total assets
age	firm age, measured as the difference between the current quarter and the IPO quarter, or, if no IPO date was available, the first occurrence in Compustat
mkshr	market share, measured as firm sales divided by total sales of 4-digit GICS industry
lawsuit	dummy variable, 1 if the firm was the target of a disclosure-related lawsuit in the previous quarter, 0 otherwise
CEOleave	dummy variable, 1 if the CEO leaves within one year after the current quarter, 0 otherwise
sprank	credit rating, measured as a numeric value (0-7) of the Standard & Poor's ranking

Table 1
Descriptive Statistics

This table shows the descriptive statistics of the variables in the sample period from 2015 to 2018. All variables except *twsentavg*, *issq*, *lawsuit*, *CEOleave*, and *sprank* have been winsorized at the 1.99% and 98.01% levels. *instcsho, laginstcsho*, *twitcnt, twitcntpos*, *twitcntneg*, and *twitcntntr* are the raw values of the variables above them to convey a more intuitive picture of the sample. All variables are defined in the appendix.

Institutional Ownership Measures						
Variable	**n**	**Mean**	**Std. Dev.**	**25th Perc.**	**Median**	**75th Perc.**
instcshochng	6516	-0.06	0.14	-0.27	-0.01	0.02
linstcsho	6516	-0.37	0.72	-0.51	-0.07	0.05
instcsho	6516	0.69	2.050	0.60	0.93	1.05
laglinstcsho	6516	-0.37	0.72	-0.51	-0.07	0.05
laginstcsho	6516	0.69	2.050	0.60	0.93	1.05
Twitter Disclosure and Sentiment Measures						
Variable	**n**	**Mean**	**Std. Dev.**	**25th Perc.**	**Median**	**75th Perc.**
ltwitcnt	6516	6.55	1.02	5.96	6.29	6.76
twitcnt	6516	698.87	2.77	388.00	537.00	859.00
ltwitcntpos	6516	5.64	1.06	4.95	5.40	6.00
twitcntpos	6516	280.18	2.88	141.00	221.50	404.00
ltwitcntneg	6516	5.29	1.03	4.70	5.04	5.48
twitcntneg	6516	198.60	2.81	110.00	154.00	239.00
ltwitcntntr	6516	6.79	1.55	5.76	6.47	7.26
twitcntntr	6516	886.74	4.73	318.00	643.00	1416.00
twsentavg	6516	0.04	0.06	<0.01	0.03	0.06
twsentmin	6516	-0.54	0.25	-0.70	-0.51	-0.35
twsentmax	6516	0.63	0.24	0.45	0.63	0.84
Control Variables						
Variable	**n**	**Mean**	**Std. Dev.**	**25th Perc.**	**Median**	**75th Perc.**
comother	6516	5.18	3.51	3.00	4.00	7.00
comsec	6516	10.02	6.74	5.00	8.00	13.00
compress	6516	29.40	45.68	8.00	15.00	29.00
issq	6516	4.90	2.87	2.08	4.70	7.00
CEOequity	6516	0.02	0.06	<0.01	<0.01	0.01
CEOstkcomp	6516	0.48	0.43	0.20	0.45	0.64
adex	6516	0.01	0.01	<0.01	<0.01	0.01
leverage	6516	0.28	0.23	0.08	0.25	0.41
size	6516	8.05	1.63	6.88	7.82	9.10
mb	6516	1.96	1.63	0.84	1.47	2.57
age	6516	29.74	18.80	17.00	24.00	44.00
mkshr	6516	0.01	0.03	<0.01	<0.01	0.01
lawsuit	6516	0.01	0.10	<0.01	<0.01	<0.01
CEOleave	6516	0.11	0.31	<0.01	<0.01	<0.01
sprank	6516	4.88	2.17	4.00	5.00	6.00

Table 2
Correlations

This table shows the two-way Pearson correlations between the main variables of interest. Reported estimates are significant at $p < 0.10$ (*), $p < 0.05$ (**), and $p < 0.01$ (***), respectively. All variables are defined in the appendix.

	Variable	1.	2.	3.	4.	5.	6.	7.	8.	9.
1.	**instcshochng**									
2.	**linstcsho**	0.698***								
3.	**laglinstcsho**	0.585***	0.655***							
4.	**ltwitcnt**	0.061***	0.047***	0.044***						
5.	**ltwitcntpos**	0.062***	0.051***	0.042***	0.962***					
6.	**ltwitcntneg**	0.056***	0.039***	0.043***	0.976***	0.884***				
7.	**ltwitcntntr**	0.047***	0.032***	0.029**	0.929***	0.911***	0.895***			
8.	**twsentavg**	0.009	0.005	-0.018	-0.093***	0.057***	-0.210***	-0.132***		
9.	**twsentmin**	-0.027**	-0.004	-0.022*	-0.595***	-0.528***	-0.616***	-0.571***	0.181***	
10.	**twsentmax**	0.041***	0.031**	0.021*	0.541***	0.638***	0.438***	0.550***	0.192***	-0.535***

Table 3, Panel A

Results of OLS Regressions of Institutional Ownership on Twitter Variables

This table shows the results of OLS regressions, based on the White (1980) heteroskedasticity robust estimates and *p*-values. Reported estimates are significant at $p < 0.10$ (*), $p < 0.05$ (**), and $p < 0.01$ (***), respectively. Industry-fixed effects are based on the 4-digit GICS classification. All variables are defined in the appendix.

Variable	(1)	(2)	(3)	(4)
intercept	**-0.422*** **	**-0.424*** **	**-0.369*** **	**-0.375*** **
	(-4.10)	(-4.17)	(-3.67)	(-3.72)
ltwitcnt	**0.020*** **			
	(3.85)			
ltwitcntpos		**0.024*** **		
		(4.54)		
ltwitcntneg			**0.015*** **	
			(2.87)	
ltwitcntntr				**0.012*** **
				(3.18)
laglinstcsho	**0.640*** **	**0.640*** **	**0.640*** **	**0.640*** **
	(37.71)	(37.71)	(37.75)	(37.78)
comother	**>-0.001**	**-0.001**	**>-0.001**	**-0.001**
	(-0.20)	(-0.23)	(-0.17)	(-0.22)
comsec	**0.003*** **	**0.003*** **	**0.003*** **	**0.003*** **
	(3.42)	(3.37)	(3.43)	(3.42)
compress	**>-0.001**	**>-0.001**	**>-0.001**	**>-0.001**
	(-0.36)	(-0.34)	(-0.38)	(-0.37)
issq	**0.003**	**0.003**	**0.003**	**0.003**
	(1.14)	(1.16)	(1.12)	(1.11)
CEOequity	**-0.246** **	**-0.245** **	**-0.248** **	**-0.243** **
	(-2.40)	(-2.38)	(-2.41)	(-2.37)
CEOstkcomp	**0.017**	**0.017**	**0.017**	**0.016**
	(1.03)	(1.04)	(1.02)	(0.98)
adex	**-1.138**	**-1.150**	**-1.124**	**-1.115**
	(-1.52)	(-1.54)	(-1.51)	(-1.49)
leverage	**0.052* **	**0.052* **	**0.052* **	**0.053* **
	(1.65)	(1.66)	(1.65)	(1.69)
size	**0.012* **	**0.013* **	**0.012**	**0.012* **
	(1.68)	(1.73)	(1.63)	(1.67)
mb	**0.008* **	**0.008* **	**0.008* **	**0.008* **
	(1.90)	(1.95)	(1.84)	(1.88)
age	**-0.001** **	**-0.001** **	**-0.001** **	**-0.001** **
	(-2.14)	(-2.15)	(-2.13)	(-2.17)
mkshr	**-0.776* **	**-0.792* **	**-0.751* **	**-0.766* **
	(-1.71)	(-1.74)	(-1.65)	(-1.69)
lawsuit	**0.063**	**0.063**	**0.064**	**0.063**
	(1.47)	(1.45)	(1.48)	(1.47)
CEOleave	**-0.011**	**-0.012**	**-0.011**	**-0.012**
	(-0.54)	(-0.55)	(-0.53)	(-0.54)
sprank	**-0.006* **	**-0.006* **	**-0.006* **	**-0.006* **
	(-1.86)	(-1.91)	(-1.83)	(-1.80)
year FE	yes	yes	yes	yes
industry FE	yes	yes	yes	yes
n	6516	6516	6516	6516
adjusted R^2	0.464	0.464	0.464	0.464

Table 3, Panel B
Results of OLS Regressions of Institutional Ownership on Twitter Variables

This table shows the results of OLS regressions, based on the White (1980) heteroskedasticity robust estimates and *p*-values. Reported estimates are significant at $p < 0.10$ (*), $p < 0.05$ (**), and $p < 0.01$ (***), respectively. Industry-fixed effects are based on the 4-digit GICS classification. All variables are defined in the appendix.

Variable	(1)	(2)	(3)	(4)
intercept	**-0.084***** (-3.61)	**-0.080***** (-3.48)	**-0.074***** (-3.26)	**-0.073***** (-3.27)
ltwitcnt	**0.006***** (3.97)			
ltwitcntpos		**0.006***** (4.17)		
ltwitcntneg			**0.005***** (3.58)	
ltwitcntntr				**0.004***** (3.93)
laglinstcsho	**0.113***** (38.66)	**0.113***** (38.66)	**0.113***** (38.69)	**0.113***** (38.74)
comother	**-0.001** (-1.16)	**-0.001** (-1.17)	**-0.001** (-1.14)	**-0.001** (-1.20)
comsec	**<0.001** (1.54)	**<0.001** (1.48)	**<0.001** (1.59)	**<0.001** (1.55)
compress	**>-0.001** (-0.23)	**>-0.001** (-0.21)	**>-0.001** (-0.24)	**>-0.001** (-0.23)
issq	**0.001***** (2.71)	**0.001***** (2.74)	**0.001***** (2.69)	**0.001***** (2.67)
CEOequity	**0.083***** (2.95)	**0.083***** (2.96)	**0.083***** (2.95)	**0.084***** (2.99)
CEOstkcomp	**-0.001** (-0.19)	**-0.001** (-0.19)	**-0.001** (-0.19)	**-0.001** (-0.26)
adex	**-0.094** (-0.57)	**-0.095** (-0.58)	**-0.092** (-0.55)	**-0.088** (-0.53)
leverage	**-0.002** (-0.31)	**-0.002** (-0.30)	**-0.002** (-0.32)	**-0.002** (-0.26)
size	**0.001** (0.70)	**0.001** (0.73)	**0.001** (0.66)	**0.001** (0.71)
mb	**0.004***** (3.75)	**0.004***** (3.77)	**0.004***** (3.71)	**0.004***** (3.75)
age	**<0.001** (0.27)	**<0.001** (0.27)	**<0.001** (0.28)	**<0.001** (0.22)
mkshr	**0.070** (0.75)	**0.070** (0.75)	**0.073** (0.78)	**0.071** (0.75)
lawsuit	**0.016** (1.57)	**0.016** (1.57)	**0.016** (1.57)	**0.016** (1.57)
CEOleave	**-0.002** (-0.49)	**-0.002** (-0.50)	**-0.002** (-0.48)	**-0.002** (-0.50)
sprank	**-0.002*** (-1.90)	**-0.002*** (-1.94)	**-0.001*** (-1.87)	**-0.001*** (-1.83)
year FE	yes	yes	yes	yes
industry FE	yes	yes	yes	yes
n	6516	6516	6516	6516
adjusted R^2	0.353	0.353	0.353	0.353

Table 4
Univariate Comparison of Institutional Ownership
in the Weeks Before and After Tweet Character Increase on November 7, 2017

This table shows the results of means-difference *t*-tests. Reported estimates are significant at $p < 0.10$ (*), $p < 0.05$ (**), and $p < 0.01$ (***), respectively. All variables are defined in the appendix. Institutional ownership and the changes in institutional ownership are compared in the week before and the week after November 7, 2017. On that day, Twitter doubled its character limit per Tweet from 180 to 360 characters.

	Before		**After**				
	Mean	**n**	**Mean**	**n**	**Means Difference**	***t*-Statistic**	***p*-Value**
linstcsho	-0.063	1166	-0.061	1130	0.002	-0.216	0.414
instcshochng	<0.001	1166	0.002	1130	0.001	-1.316	0.094

Table 5, Panel A
Results of Difference-in-Difference Regressions of Institutional Ownership on Twitter Variables

This table shows the results of difference-in-difference regressions, based on the White (1980) heteroskedasticity robust estimates and *p*-values. Reported estimates are significant at $p < 0.10$ (*), $p < 0.05$ (**), and $p < 0.01$ (***), respectively. Industry-fixed effects are based on the 4-digit GICS classification. All variables are defined in the appendix.

Variable	(1)	(2)	(3)	(4)
intercept	0.336	0.277	0.300	0.216
	(1.27)	(1.06)	(1.16)	(0.83)
DiDcnt	0.067***			
	(3.19)			
ltwitcnt	-0.038***			
	(-2.68)			
DiDpos		0.076***		
		(3.39)		
ltwitcntpos		-0.035**		
		(-2.41)		
DiDneg			0.049**	
			(2.22)	
ltwitcntneg			-0.040***	
			(-2.79)	
DiDntr				0.033**
				(2.00)
ltwitcntntr				-0.020*
				(-1.67)
eventqtr	-0.511***	-0.496***	-0.336***	-0.296**
	(-3.59)	(-3.89)	(-2.68)	(-2.49)
laglinstcsho	0.797***	0.796***	0.798***	0.797***
	(27.48)	(27.46)	(27.62)	(27.45)
comother	-0.004	-0.004	-0.004	-0.004
	(-0.74)	(-0.77)	(-0.72)	(-0.73)
comsec	0.002	0.002	0.002	0.002
	(0.85)	(0.85)	(0.83)	(0.86)
compress	>-0.001	>-0.001	>-0.001	-0.001
	(-1.05)	(-1.09)	(-1.05)	(-1.09)
issq	-0.006	-0.006	-0.006	-0.006
	(-1.16)	(-1.19)	(-1.15)	(-1.11)
CEOequity	-0.190	-0.198	-0.178	-0.191
	(-0.81)	(-0.84)	(-0.76)	(-0.81)
CEOstkcomp	0.053	0.053	0.054	0.054
	(1.40)	(1.39)	(1.41)	(1.40)
adex	1.702	1.678	1.696	1.702
	(0.97)	(0.95)	(0.97)	(0.97)
leverage	-0.024	-0.023	-0.023	-0.025
	(-0.33)	(-0.32)	(-0.32)	(-0.34)
size	0.036**	0.037**	0.035**	0.035**
	(2.22)	(2.28)	(2.17)	(2.21)
mb	0.009	0.010	0.009	0.009
	(0.99)	(1.04)	(0.95)	(0.97)
age	-0.001	-0.001	-0.001	-0.001
	(-0.70)	(-0.67)	(-0.67)	(-0.70)
mkshr	0.038	0.003	0.101	0.063
	(0.04)	(<0.01)	(0.10)	(0.06)
lawsuit	0.164	0.157	0.171	0.172
	(0.86)	(0.85)	(0.89)	(0.90)
CEOleave	-0.050	-0.052	-0.049	-0.049
	(-1.19)	(-1.25)	(-1.15)	(-1.15)
sprank	-0.001	-0.001	-0.001	-0.001
	(-0.14)	(-0.17)	(-0.14)	(-0.13)
year FE	no	no	no	no
industry FE	yes	yes	yes	yes
n	873	873	873	873
adjusted R^2	0.647	0.648	0.647	0.646

Table 5, Panel B

Results of Difference-in-Difference Regressions of Changes in Institutional Ownership on Twitter Variables

This table shows the results of difference-in-difference regressions, based on the White (1980) heteroskedasticity robust estimates and *p*-values. Reported estimates are significant at $p < 0.10$ (*), $p < 0.05$ (**), and $p < 0.01$ (***), respectively. Industry-fixed effects are based on the 4-digit GICS classification. All variables are defined in the appendix.

Variable	(1)	(2)	(3)	(4)
intercept	**0.118***	**0.111***	**0.113***	**0.106***
	(1.86)	(1.81)	(1.86)	(1.79)
DiDcnt	**0.018****			
	(2.30)			
ltwitcnt	**-0.005**			
	(-1.07)			
DiDpos		**0.021****		
		(2.57)		
ltwitcntpos		**-0.004**		
		(-0.94)		
DiDneg			**0.012**	
			(1.58)	
ltwitcntneg			**-0.005**	
			(-1.18)	
DiDntr				**0.012****
				(2.29)
ltwitcntntr				**-0.003**
				(-1.00)
eventqtr	**-0.034**	**-0.034**	**0.016**	**-0.001**
	(-0.70)	(-0.77)	(0.41)	(-0.04)
laglinstcsho	**0.181*****	**0.181*****	**0.182*****	**0.182*****
	(38.72)	(38.83)	(39.21)	(38.87)
comother	**0.001**	**0.001**	**0.001**	**0.001**
	(0.66)	(0.63)	(0.70)	(0.66)
comsec	**0.001****	**0.001****	**0.001****	**0.001****
	(2.12)	(2.11)	(2.10)	(2.16)
compress	**>-0.001**	**>-0.001**	**>-0.001**	**>-0.001**
	(-1.07)	(-1.08)	(-1.09)	(-1.09)
issq	**0.001**	**0.001**	**0.001**	**0.001**
	(1.00)	(0.96)	(1.03)	(1.01)
CEOequity	**-0.036**	**-0.038**	**-0.032**	**-0.037**
	(-0.38)	(-0.40)	(-0.34)	(-0.39)
CEOstkcomp	**0.002**	**0.002**	**0.002**	**0.001**
	(0.33)	(0.29)	(0.38)	(0.25)
adex	**0.158**	**0.156**	**0.153**	**0.160**
	(0.42)	(0.42)	(0.41)	(0.43)
leverage	**-0.026**	**-0.025**	**-0.026**	**-0.025**
	(-1.43)	(-1.42)	(-1.42)	(-1.42)
size	**-0.001**	**-0.001**	**-0.001**	**-0.001**
	(-0.24)	(-0.19)	(-0.31)	(-0.30)
mb	**0.001**	**0.002**	**0.001**	**0.001**
	(0.60)	(0.66)	(0.55)	(0.56)
age	**<0.001**	**<0.001**	**<0.001**	**<0.001**
	(1.25)	(1.28)	(1.27)	(1.20)
mkshr	**0.138**	**0.133**	**0.154**	**0.146**
	(0.71)	(0.69)	(0.79)	(0.75)
lawsuit	**-0.021**	**-0.022**	**-0.020**	**-0.019**
	(-1.30)	(-1.34)	(-1.23)	(-1.19)
CEOleave	**0.022***	**0.022***	**0.023***	**0.023***
	(1.85)	(1.82)	(1.87)	(1.89)
sprank	**-0.003**	**-0.003**	**-0.003**	**-0.003**
	(-1.39)	(-1.45)	(-1.36)	(-1.36)
year FE	no	no	no	no
industry FE	yes	yes	yes	yes
n	873	873	873	873
adjusted R^2	0.662	0.664	0.661	0.662

Table 6, Panel A
Results of OLS Regressions of Institutional Ownership on Twitter Valence Variables

This table shows the results of OLS regressions, based on the White (1980) heteroskedasticity robust estimates and *p*-values. Reported estimates are significant at $p < 0.10$ (*), $p < 0.05$ (**), and $p < 0.01$ (***), respectively. Industry-fixed effects are based on the 4-digit GICS classification. All variables are defined in the appendix.

Variable	(1)	(2)	(3)	(4)	(5)
intercept	**-0.297*** **	**-0.313*** **	**-0.290*** **	**-0.348*** **	**-0.295*** **
	(-3.06)	(-3.19)	(-2.99)	(-3.53)	(-3.03)
twsentavg	**0.226***				
	(1.86)				
twsentpos		**0.023**			
		(1.44)			
twsentneg			**-0.023**		
			(-1.44)		
twsentmax				**0.099*** **	
				(3.40)	
twsentmin					**-0.005**
					(-0.19)
laglinstcsho	**0.642*** **	**0.640*** **	**0.640*** **	**0.640*** **	**0.641*** **
	(37.94)	(37.72)	(37.72)	(37.81)	(37.88)
comoth	**>-0.001**	**>-0.001**	**>-0.001**	**>-0.001**	**>-0.001**
	(-0.10)	(-0.13)	(-0.13)	(-0.14)	(-0.11)
comsec	**0.003*** **	**0.003*** **	**0.003*** **	**0.003*** **	**0.003*** **
	(3.26)	(3.30)	(3.30)	(3.31)	(3.36)
compress	**>-0.001**	**>-0.001**	**>-0.001**	**>-0.001**	**>-0.001**
	(-0.41)	(-0.41)	(-0.41)	(-0.40)	(-0.40)
issq	**0.003**	**0.003**	**0.003**	**0.003**	**0.003**
	(1.18)	(1.24)	(1.24)	(1.17)	(1.14)
CEOequity	**-0.254** **	**-0.253** **	**-0.253** **	**-0.252** **	**-0.254** **
	(-2.47)	(-2.46)	(-2.46)	(-2.45)	(-2.47)
CEOstkcomp	**0.017**	**0.017**	**0.017**	**0.016**	**0.016**
	(1.01)	(1.02)	(1.02)	(0.93)	(0.99)
adex	**-1.114**	**-1.106**	**-1.106**	**-1.078**	**-1.095**
	(-1.50)	(-1.48)	(-1.48)	(-1.44)	(-1.47)
leverage	**0.052***	**0.053***	**0.053***	**0.057***	**0.053***
	(1.65)	(1.70)	(1.70)	(1.82)	(1.67)
size	**0.011**	**0.012**	**0.012**	**0.012***	**0.011**
	(1.57)	(1.59)	(1.59)	(1.65)	(1.55)
mb	**0.007***	**0.007***	**0.007***	**0.008***	**0.007***
	(1.71)	(1.77)	(1.77)	(1.86)	(1.74)
age	**-0.001** **	**-0.001** **	**-0.001** **	**-0.001** **	**-0.001** **
	(-2.07)	(-2.06)	(-2.06)	(-2.21)	(-2.09)
mkshr	**-0.667**	**-0.663**	**-0.663**	**-0.733**	**-0.684**
	(-1.47)	(-1.47)	(-1.47)	(-1.62)	(-1.51)
lawsuit	**0.066**	**0.066**	**0.066**	**0.062**	**0.064**
	(1.51)	(1.51)	(1.51)	(1.43)	(1.49)
CEOleave	**-0.012**	**-0.013**	**-0.013**	**-0.013**	**-0.012**
	(-0.54)	(-0.63)	(-0.63)	(-0.61)	(-0.54)
sprank	**-0.006***	**-0.006***	**-0.006***	**-0.006***	**-0.006***
	(-1.88)	(-1.93)	(-1.93)	(-1.87)	(-1.83)
year FE	yes	yes	yes	yes	yes
industry FE	yes	yes	yes	yes	yes
n	6516	6499	6499	6516	6516
adjusted R^2	0.463	0.462	0.462	0.464	0.463

Table 6, Panel B

Results of OLS Regressions of Changes in Institutional Ownership on Twitter Valence Variables

This table shows the results of OLS regressions, based on the White (1980) heteroskedasticity robust estimates and *p*-values. Reported estimates are significant at $p < 0.10$ (*), $p < 0.05$ (**), and $p < 0.01$ (***), respectively. Industry-fixed effects are based on the 4-digit GICS classification. All variables are defined in the appendix.

Variable	(1)	(2)	(3)	(4)	(5)
intercept	**-0.049****	**-0.053****	**-0.046****	**-0.059*****	**-0.051****
	(-2.24)	(-2.43)	(-2.13)	(-2.68)	(-2.37)
twsentavg	**0.043**				
	(1.51)				
twsentpos		**0.006***			
		(1.76)			
twsentneg			**-0.006***		
			(-1.76)		
twsentmax				**0.020*****	
				(2.98)	
twsentmin					**-0.009**
					(-1.46)
laglinstcsho	**0.114*****	**0.113*****	**0.113*****	**0.113*****	**0.113*****
	(38.96)	(38.72)	(38.72)	(38.81)	(38.84)
comoth	**-0.001**	**-0.001**	**-0.001**	**-0.001**	**-0.001**
	(-1.03)	(-1.02)	(-1.02)	(-1.07)	(-1.04)
comsec	**<0.001**	**<0.001**	**<0.001**	**<0.001**	**<0.001**
	(1.40)	(1.40)	(1.40)	(1.42)	(1.52)
compress	**>-0.001**	**>-0.001**	**>-0.001**	**>-0.001**	**>-0.001**
	(-0.30)	(-0.32)	(-0.32)	(-0.28)	(-0.30)
issq	**0.001*****	**0.002*****	**0.002*****	**0.001*****	**0.001*****
	(2.75)	(2.78)	(2.78)	(2.74)	(2.68)
CEOequity	**0.081*****	**0.081*****	**0.081*****	**0.081*****	**0.081*****
	(2.87)	(2.88)	(2.88)	(2.89)	(2.88)
CEOstkcomp	**-0.001**	**-0.001**	**-0.001**	**-0.001**	**-0.001**
	(-0.23)	(-0.22)	(-0.22)	(-0.30)	(-0.26)
adex	**-0.086**	**-0.085**	**-0.085**	**-0.079**	**-0.079**
	(-0.52)	(-0.51)	(-0.51)	(-0.47)	(-0.48)
leverage	**-0.002**	**-0.002**	**-0.002**	**-0.001**	**-0.002**
	(-0.30)	(-0.25)	(-0.25)	(-0.16)	(-0.25)
size	**0.001**	**0.001**	**0.001**	**0.001**	**0.001**
	(0.56)	(0.55)	(0.55)	(0.62)	(0.55)
mb	**0.004*****	**0.004*****	**0.004*****	**0.004*****	**0.004*****
	(3.56)	(3.59)	(3.59)	(3.69)	(3.61)
age	**<0.001**	**<0.001**	**<0.001**	**<0.001**	**<0.001**
	(0.36)	(0.37)	(0.37)	(0.23)	(0.30)
mkshr	**0.100**	**0.104**	**0.104**	**0.087**	**0.091**
	(1.07)	(1.12)	(1.12)	(0.93)	(0.98)
lawsuit	**0.017**	**0.017**	**0.017**	**0.016**	**0.016**
	(1.62)	(1.62)	(1.62)	(1.56)	(1.60)
CEOleave	**-0.002**	**-0.002**	**-0.002**	**-0.003**	**-0.002**
	(-0.50)	(-0.55)	(-0.55)	(-0.56)	(-0.52)
sprank	**-0.002***	**-0.002***	**-0.002***	**-0.002***	**-0.001***
	(-1.90)	(-1.93)	(-1.93)	(-1.89)	(-1.84)
year FE	yes	yes	yes	yes	yes
industry FE	yes	yes	yes	yes	yes
n	6516	6499	6499	6516	6516
adjusted R^2	0.352	0.351	0.351	0.352	0.352

Table 7

Propensity Score Matching of Different Levels and Changes in Institutional Ownership on Twitter Variables

This table shows the results of probit regressions and propensity score matching. The estimated effect size is reported below the respective first-step probit regression coefficient estimates. Reported estimates are significant at $p < 0.10$ (*), $p < 0.05$ (**), and $p < 0.01$ (***), respectively. All variables are defined in the appendix. *twpubint* compares the highest and lowest septile of Twitter disclosure levels. The remaining columns compare firm-quarters that saw an increase (decrease) by 1.5, 2, 2.5, and 3 times the Twitter disclosure of the previous quarter to all other firm-quarters.

Variable	twpubint	twpub+1.5	twpub+2	twpub+2.5	twpub+3	twpub-1.5	twpub-2	twpub-2.5	twpub-3
intercept	**1.122*****	**-1.083*****	**-1.433*****	**-1.603*****	**-2.205*****	**-1.061*****	**-1.243*****	**-2.209*****	**-2.813*****
	(5.02)	(-6.65)	(-5.54)	(-5.16)	(-5.11)	(-7.04)	(-5.86)	(-6.21)	(-5.87)
issq	**0.008**	**0.008**	**0.005**	**-0.007**	**-0.020**	**0.009**	**0.006**	**0.020**	**0.028**
	(0.75)	(1.07)	(0.42)	(-0.48)	(-0.97)	(1.22)	(0.58)	(1.19)	(1.25)
CEOequity	**0.295**	**-0.232**	**-0.292**	**0.246**	**1.130**	**-0.098**	**0.366**	**-0.794**	**0.366**
	(0.47)	(-0.53)	(-0.43)	(0.33)	(1.25)	(-0.25)	(0.70)	(-0.75)	(0.35)
CEOstkcomp	**0.079**	**0.026**	**0.041**	**0.045**	**-0.005**	**0.037**	**0.045**	**0.074**	**-0.102**
	(1.15)	(0.52)	(0.54)	(0.50)	(-0.03)	(0.80)	(0.71)	(0.71)	(-0.59)
adex	**2.728**	**-0.843**	**0.490**	**-2.537**	**-8.392**	**1.590**	**0.984**	**-0.122**	**-1.903**
	(0.96)	(-0.39)	(0.15)	(-0.63)	(-1.26)	(0.83)	(0.37)	(-0.03)	(-0.30)
size	**-0.184*****	**-0.033**	**-0.082****	**-0.065**	**-0.006**	**-0.018**	**-0.071*****	**-0.030**	**0.023**
	(-6.64)	(-1.62)	(-2.47)	(-1.64)	(-0.11)	(-0.96)	(-2.65)	(-0.68)	(0.38)
mb	**-0.072*****	**-0.011**	**0.004**	**0.006**	**0.016**	**-0.005**	**-0.023**	**-0.001**	**0.030**
	(-3.79)	(-0.78)	(0.18)	(0.25)	(0.46)	(-0.40)	(-1.18)	(-0.03)	(0.84)
age	**0.008*****	**-0.001**	**<0.001**	**-0.001**	**-0.002**	**>-0.001**	**>-0.001**	**0.002**	**-0.001**
	(4.05)	(-0.81)	(0.17)	(-0.52)	(-0.64)	(-0.06)	(-0.16)	(0.68)	(-0.12)
mkshr	**7.713*****	**0.402**	**0.703**	**-0.365**	**-4.451**	**-0.398**	**1.895**	**-0.617**	**-4.426**
	(5.68)	(0.37)	(0.38)	(-0.15)	(-0.97)	(-0.40)	(1.37)	(-0.24)	(-0.96)
sprank	**0.008**	**0.013**	**0.007**	**-0.002**	**-0.003**	**0.007**	**0.008**	**-0.010**	**-0.010**
	(0.50)	(1.14)	(0.36)	(-0.07)	(-0.11)	(0.69)	(0.51)	(-0.41)	(-0.31)
atet (linstcsho)	**0.126*****	**0.049**	**0.015**	**0.070**	**0.079**	**-0.048**	**-0.047**	**0.008**	**0.028**
	(2.98)	(1.28)	(0.21)	(0.74)	(0.55)	(-1.44)	(-0.86)	(0.07)	(0.20)
atet (instcshochng)	**0.020****	**0.010**	**>-0.001**	**0.043****	**0.068****	**0.014****	**0.027****	**0.037**	**0.041**
	(2.08)	(1.19)	(-0.01)	(2.12)	(2.34)	(2.01)	(2.26)	(1.36)	(1.26)
n	1849	6516	6516	6516	6516	6516	6516	6516	6516