The Emergence of "Social Executives" and Its Consequences for Financial Markets

We document the emergence of "social executives," top executives who connect with investors directly, personally, and in real time through social media, and we study the consequences of this development for financial markets. We contend that the emergence of social executives enables retail investors to obtain value-relevant information to which they previously had no access. Social executives also grab investor attention. Building on the finance market microstructure literature, we argue that both improving access to value-relevant information and attracting investor attention help widen a firm's retail investor base and improve stock market liquidity. Using data reflecting the personal Twitter account activity of the CEOs and CFOs of the largest publicly traded companies in the United States, we find evidence consistent with our argument. Utilizing the Securities and Exchange Commission's recent embrace of social media as a plausibly exogenous shock, we also provide evidence for a causal link. We conclude that the emergence of social executives has important consequences for financial markets.

Keywords: Social executives, Social Media, Retail Investors, Stock Markets

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1. INTRODUCTION

The media is filled with anecdotal accounts of corporate executives that are active on social media and the popular press is not shy about giving advice to executives on how to best manage their social media presence (Kasian-Lew 2014; Hootsuite 2017). In this study, we systematically document the emergence of "social executives," top executives who connect with followers directly, personally, and in real time through social media. We then assess the economic consequences of this recent development for financial markets. We first develop theoretical arguments that predict how financial markets will react to the emergence of social executives. Our theory focuses on the use of Twitter, the most widely adopted social media platform by top executives, but our arguments should easily extend to alternate social media outlets. We then test our hypotheses using novel data reflecting personal tweets from CEOs/CFOs of the largest publicly traded companies in the United States.

Our theoretical framework encompasses two complementary theories. As we discuss in greater detail here, CEOs and CFOs use their own personal Twitter accounts to (a) break company news, (b) describe their work-related day-to-day activities, and (c) share their unrelated-to-work personal interests and moods.

In our first theory, we speculate that personal tweets of top executives contain the occasional piece of "hard information" that is independent of public press releases or regulatory filings as top executives' firms do not consider the information material enough. More importantly, we conjecture that personal tweets describing an executive's work-related day-to-day activities contain much unique and value-relevant "soft information." Consistent with this view, we find that

top executives' personal tweets describing work-related day-to-day activities help predict future earnings and strongly and permanently move stock prices. As any investor can choose to follow any public Twitter account, top executives' Twitter accounts represent "democratic access" to unique and value-relevant information.

Professional investors, also known as institutional investors, have always had access to top executives through one-on-one meetings with top executives. In the United States, the average publicly traded firm conducts 153 private meetings a year, with a top executive taking part in 90 of them (Investor Relations Magazine 2015). If one were to include phone calls between institutional investors and top executive, the number of private meetings would be significantly higher (Soltes 2014).

Prior literature notes that attendees at such private meetings obtain novel hard information (Bengtzen 2017; Park and Soltes 2018). Attendees at such private meetings also source much soft information based on a top executive's tone and body language (Wall Street Journal 2015) or responses to broad and personal questions posed (Park and Soltes 2018). Overall, attendees consistently rank private meetings as their most useful means of staying informed (Brown et al. 2016), and evidence suggests that investors earn significant trading profits by attending such meetings (Solomon and Soltes 2015). As we explain in Section 3.1, unlike Twitter accounts, access to private meetings is not democratic and, instead, exclusive to the largest institutional investors. The presence of private meetings and the unequal access to them therefore generate an unlevel playing field for investors.

In this paper we argue that while the presence of social executives is clearly no substitute to private meetings with top executives, the emergence of social executives still marks a democratization of access to unique and value-relevant information to which most investors

previously had no access. We therefore argue that the playing field has become more level with the emergence of social executives.

The emergence of social executives may matter for another reason. There are well over 4,000 stocks and more than 18,000 funds to which investors can allocate money (Doidge et al. 2017; Investment Company Fact Book 2017). Prior studies note that, faced with such a myriad of investment opportunities, some investors consider only options that have salient attributes that grab their attention (Hirshleifer 2001; Barber and Odean 2008). In our second theory, we conjecture that social executives represent one such salient attribute.

A key ingredient of the investor attention framework is that investors who are most affected by salient attributes are thought to be retail investors, not well-informed large institutional investors (e.g., Grullon et al. 2004; Barber and Odean 2008; Da et al. 2011). Moreover, attention-generating events themselves need not be substantive, and, in general, they are presumed not to be substantive. As a result, the trades induced by attention-generating events and the investors placing those trades are likely to be uninformed (e.g., Grullon et al. 2004; Barber and Odean 2008; Da et al. 2011). In line with this view, we find that, while top executives' tweets about their personal interests and moods are uncorrelated with future earnings, some investors nevertheless react to such tweets, presumably because they provide entertainment value and grab investor attention. We further provide evidence that any price reaction tied to such tweets subsequently reverses, consistent with these uninformed investors creating mispricing that subsequently corrects itself (Da et al. 2011).

The finance market microstructure literature shows that both a more even playing field and greater participation on the part of relatively uninformed retail investors improve stock market liquidity (e.g., O'Hara 1995; Harris 2003; Madhavan 2000). The intuition is that, in the presence

of investors with private information, the remaining investor population cannot be confident that any stock transaction occurs at a "fair price." As a result, stock market liquidity dries up. As the playing field becomes more level and as more investors who lack relevant information enter the market, the risk of trading against informationally superior investors declines. In response, stock market liquidity improves.

To test our predictions, we examine the personal Twitter accounts of the CEOs and CFOs of the largest publicly traded companies in the United States. Our sample includes, in particular, firms that participate in the Standard & Poor's 1500 Composite Index (S&P 1500). The S&P 1500 represents more than 90% of total U.S. stock market capitalization. Our analysis begins in April 2008, when the first personal tweet from an S&P 1500 top executive was sent and it ends in December 2014. In total, our sample includes 155 CEOs and CFOs working for 142 firms who sent a total of 47,119 tweets. As of December 2014, these 142 firms had a combined market capitalization of $3.4 trillion, or 15% of the total market capitalization across all S&P 1500 firms at that time.

Following prior literature, we capture liquidity via bid–ask spreads, depth, and turnover (e.g., Coller and Yohn 1997; Leuz and Verrecchia 2000; Lang et al. 2012) and we test within a difference-in-differences framework whether stock market liquidity and investor base change as a result of a top executive's becoming social.

Consistent with our prediction, we find that in the year after a top executive becomes social the corresponding bid–ask spread disproportionately drops by 0.024% compared with the bid–ask spread in the year prior to the executive's becoming social. The corresponding depth disproportionately rises by 1.8% and the corresponding daily turnover disproportionately rises by 0.014%. Bid–ask spreads represent a significant trading cost to investors (e.g., Harris 2003). A

decrease in spreads of 0.024%, which—considering the average spread prior to the emergence of a social executive—translates into a 21.6 percentage points decrease in spreads, is therefore an economically substantial result. Similarly, the observed rise in daily turnover suggests that an additional 0.51 million shares are being traded per day as a result of a top executive's becoming social. We also find that when a top executive becomes social the corresponding firm's retail investor base grows disproportionately by 12.6 percentage points. We observe no significant change in the number of institutional investors.

Additional analyses reveal that our results become stronger (both statistically and economically) when the corresponding top executive posts more tweets, receives more retweets, or attracts more followers. Our results are also significantly stronger when an executive uses Twitter to describe mostly work-related day-to-day activities as opposed to personal interests and moods. The result from the latter analysis suggests that our stock market liquidity and investor base results are perhaps better captured by our first "Leveling the Playing Field" theory than our second "Grabbing Investor Attention" theory.

Executives do not become social randomly and we are mindful of the resulting self-selection bias concern. In our difference-in-differences analysis, we implement both propensity-score matching and the Heckman correction procedure to address this concern. In particular, we first estimate a cross-sectional Probit model to predict a top executive's decision to adopt Twitter based on a host of observable executive and firm characteristics. We build on this Probit model and find, for each treated firm that employs a social executive, a matched control firm that is observationally identical to the treated firm but whose CEO/CFO does not adopt Twitter in our study period. Our reported changes in liquidity and investor base for firms with social executives all represent changes above and beyond any changes experienced by their matched firms over the

same timeframe. To further account for self-selection bias, we follow prior literature (e.g., Heckman 1979) and treat self-selection bias as a form of omitted-variable bias. We calculate the yearly Inverse Mills Ratios (IMR) to gauge the likelihood of an executive's adopting Twitter in a given year and we include this yearly IMR measure as a control variable in all of our difference-in-differences analyses. Our results are highly robust to these procedures.

Our final test, which further addresses endogeneity concerns and enables us to compare the explanatory power of our two theories, examines how our sample firms behave around a recent Securities and Exchange Commission (SEC) ruling. In 2008, the SEC published an interpretive release regarding the use of social media to broadcast company-specific news. The release was criticized by the legal community for being vague and exposing social executives to concerns that when they use social media they are violating fair disclosure rules, also known as "Reg FD" (e.g., Davis et al. 2013). On April 2, 2013 the SEC clarified its position and "*blessed the use of social-media sites to broadcast market-moving corporate news*," meaning that "*executives with itchy Twitter fingers can* [now] *rest easier*" and be less constrained in their Twitter activity (Wall Street Journal 2013).

In line with the above characterization, we conjecture that prior to April 2, 2013 some executives were wary of tweeting content that could be construed as violating Reg FD. As a result, executives limited their use of Twitter to describe work-related day-to-day activities. After April 2, 2013, however, executives became more comfortable posting tweets that are pertinent to their firms' operations. If executives indeed became more comfortable sending work-related tweets and if, in line with our evidence, work-related tweets are more informative to investors than unrelated-to-work tweets, our "Leveling the Playing Field" theory predicts an incremental improvement in stock market liquidity and a firm's retail investor base around the SEC ruling. As any shift in

executive tweets tied to the SEC ruling is plausibly exogenous, any observed improvement would point to a causal link.

To assess the validity of our conjecture that executives became more comfortable sending work-related tweets after the SEC's clarification, we have research assistants read each tweet in our sample and categorize them as work-related or unrelated to work. In our first-stage analysis, we find that the fraction of work-related tweets posted by existing social media adopters indeed, suddenly and substantially and permanently, increases after April 2013. The fraction of unrelated-to-work tweets describing personal interests and moods declines accordingly.

In our second-stage analysis, we find this spike in work-related tweets around the SEC's announcement accompanied by an incremental decrease in spreads and incremental rises in depth, trading volume, and retail investor bases among the affected firms. The results obtained from our final analysis point to a causal link between the presence of social executives and stock market liquidity and investor bases via levelling the playing field and provide further evidence that social media adoption by top executives has important economic consequences for the underlying firms and financial markets in general.

2. Literature Review

In studying the emergence of social executives and its economic consequences, our paper contributes to the large and growing economics of information systems literature on the link between social media and firm performance. Our paper also contributes to the literature examining the use of social media by "regular" employees who operate below the top executive echelon. Finally, our hypothesis development and empirical analysis are heavily couched in the terms of the finance market microstructure literature. In this section, we briefly outline these three bodies of literature.

2.1 The Literature on Social Media and Firm Performance

The literature on the link between social media and firm performance examines the adoption and usage of social media at both the individual and firm levels in both internal and external corporate settings (e.g., Aral et al. 2013; Kane et al. 2014). Broadly speaking, the literature considers two types of firm performance—product market performance (e.g., sales, profit, customer satisfaction) and financial market performance. Some studies of product market performance focus on the social media activities of firms, or "firm-generated content" (FGC); others focus on the social media activities of consumers, or "user-generated content" (UGC).

Examining FGC, Chen et al. (2015) assess how musical artists' broadcasting activities on MySpace affect music sales. Hong et al. (2018) analyze the degree to which the fundraising outcomes of Kickstarter campaigns are jointly determined by campaigners' social media activity on Twitter, network embeddedness, and whether the campaign product is a public or private good.

Examining UGC, Aggarwal and Singh (2013) study the degree to which venture capitalists rely on blogs that cover information technology ventures at specific funding stages (e.g., screening, choice, and contract). The authors find that blog coverage helps new ventures pass the screening stage, but not necessarily the choice or contract stage. Rishika et al. (2013) show that customer activity on a firm's social networking site is positively related to the number of store visits and purchases. Differing from most related studies, which highlight the benefits of social media, Hildebrand et al. (2013) find evidence that consumer feedback transmitted through social media negatively affects design uniqueness, customer satisfaction, usage frequency, and product valuation of self-designed products in mass customization. Goh et al. (2013) and Chen et al. (2015) examine the relative effects of FGC and UGC on product sales and consumer purchases.

Most studies examining financial market performances analyze whether social media content can be used to predict future earnings or stock returns. Luo et al. (2013) consider customer reviews; Bollen et al. (2011) consider tweets; Antweiler and Frank (2004) and Park et al. (2013) consider Internet message boards; and Chen et al. (2014) and Jame et al. (2016) look at crowdsourced-equity research. These studies all conclude that social media content is useful in predicting future earnings or stock returns.

In other work, Xu and Zhang (2013) test whether user-generated social media content on Wikipedia affects a firm's "disclosure lag," which is the number of calendar days between a fiscal quarter end and the date when management voluntarily discloses bad news about earnings.

2.2 The Literature on the Use of Social Media by Firm Employees

To the best of our knowledge, ours is the first study to document social media usage by top executives. There are, however, prior studies that examine the use of social media by "regular" firm employees. Wattal et al. (2010) explore the network effects of blogging among employees. Huang et al. (2015) find that the creation of leisure-related blog posts by employees has a positive spillover effect on their consumption of work-related blog posts. Wu (2013) examines changes arising from the introduction of a social networking tool in an information technology firm and finds evidence that information-rich networks help improve work performance and job retention.

2.3 The Market Microstructure Literature

We couch our hypothesis development and empirical analysis heavily in terms of the finance market microstructure literature. There is no debating that, in financial markets, some investors enjoy an informational advantage over others. The sources of such advantages range from personal meetings with corporate executives (e.g., Soltes 2014; Brown et al. 2015; Brown et al. 2016) to

"alternative data," such as satellite imagery data that indicates the health of the latest crop, data scraped from websites revealing the latest consumer reviews of various products or services, and geolocation data from mobile phones that enable investors to track how many people frequent a given store (Financial Times 2017).

The market microstructure literature examines the economic consequences of such informational advantages. Theoretical work in this literature distinguishes between "informed traders" and "noise traders." While the former group of traders possess some private information, the latter have no special informational advantage.[1] Theories of market microstructure also include "market makers," dealers who stand ready to buy or sell stocks. Exchanges generally require the presence of dealers, as traders looking to buy stocks and traders looking to sell stocks typically do not arrive at the market at the same time. The presence of dealers overcomes the asynchronous timing of investor trades and makes continuous trading possible (e.g., O'Hara 1995; Harris 2003; Madhavan 2000).

The price at which a dealer offers to buy stock shares from traders is the bid price; the price at which a dealer offers to sell stock shares to traders is the ask price. The bid price is always lower than the ask price. The "bid–ask spread" represents a dealer's compensation for providing liquidity as well as an implicit cost to traders (Demsetz 1968, Harris 2003). Theoretical work in the market microstructure literature assumes that dealers profit from trading with noise traders due to the presence of the bid–ask spread. However, dealers lose when they trade with informed traders as a dealer buying a stock from an investor with negative private information may be forced to unload the stock at an ask price that is below the previous bid price once the negative private information becomes public; the analogue applies when a dealer sells a stock to an investor with positive private

[1] Investors with private information do not have to be (and typically are not) insider traders. Investors with private information merely represent investors who have legally obtained an informational advantage.

information. As the fraction of investors with private information increases, dealers are forced to widen the bid–ask spread to minimize their losses to informed traders. The presence of investors with private information therefore increases bid–ask spreads (Glosten and Milgrom 1985; Easley and O'Hara 1987).

While the phenomenon is less explicitly modeled, according to market microstructure theory, the presence of investors with private information lowers stock market liquidity in general (Diamond and Verrecchia 1991). The intuition behind this finding is that in the presence of investors with private information the remaining investor population cannot be confident that any stock transaction occurs at a "fair price." This not only increases the cost of trading, in the form of wider bid–ask spreads, but also decreases both the quantity of shares being offered for trade and the quantity of shares that are actually traded. The literature refers to the former as "depth" and to the latter as "trading volume, " or, if expressed as a fraction of shares outstanding, as "turnover."

Empirical work in the market microstructure area finds that spreads are wider for stocks with low market capitalization, low price per share, high volatility, and low trading volume (Stoll 2000; Holden and Jacobsen 2014). As these are the stocks thought to suffer the most from information asymmetry between informed traders and uninformed traders, the literature views the above findings as consistent with market microstructure theory. In a cross-country study, Eleswarapu and Venkataraman (2006) find evidence that liquidity increases with the quality of accounting standards. Similarly, a large body of literature in accounting provides evidence that improved corporate disclosure helps "level the playing field" among investors, thereby improving stock market liquidity (e.g., Coller and Yohn 1997; Leuz and Verrecchia 2000; Lang et al. 2012). Chordia et al. (2005) show that liquidity exhibits time-series patterns by the day of the week, the month, holidays, macroeconomic announcements, and crisis periods.

3. HYPOTHESIS DEVELOPMENT

Our framework encompasses two complementary theories. We label our first theory "Leveling the Playing Field"; we label our second theory "Grabbing Investor Attention." In this section, we lay out our theories. We test the assumptions underlying our two theories in Section 6.1.

3.1 Leveling the Playing Field

3.1.1 Institutional Investors' Exclusive Access to Top Executives

A key reason some investors enjoy an informational advantage over others is that some investors are granted exclusive access to private meetings with CEOs and CFOs, which they can use to stay informed in their companies of interest. As alluded to in the introduction, in the United States, the average publicly traded firm conducts 153 private meetings a year, with a top executive taking part in 90 of them (Investor Relations Magazine, 2015). Ninety-seven percent of CEOs in publicly traded firms report to have met privately with investors (Thomson Reuters 2009).

Using field data of over 1,200 questions asked during private meetings, Park and Soltes (2008) observe that questions asked range from the very specific, such as "How much cash do you have now?" to the broader and almost philosophical, such as "What keeps you up at night?" Responses to such questions yield the occasional "hard" piece of information (SEC 2002, 2003, 2004, 2010).[2] Responses to the broad questions and an executive's general body language and tone also provide a significant amount of "soft" information to investors (SEC 2004; WSJ 2015). Attendees consistently rank private meetings as their most important means of staying informed (Brown et al. 2016), and evidence based on proprietary data suggests that investors earn significant trading profits by attending such meetings (Solomon and Soltes 2015).

[2] Examples of such hard information include: "*new deals were coming into the sales pipeline*" or "*the company's sales pipeline was growing*" (SEC 2003).

Private meetings are generally arranged by investment banks, and investors compensate the arranging bank by routing their trades through the bank's brokerage division and paying brokerage commissions. Investors are estimated to pay $1.4 billion a year for access to private meetings (WSJ 2015). Retail investors (and perhaps even smaller institutional investors) do not gain access to these private meetings as they do not place sufficiently many trades and, therefore, do not generate enough commission-based income for banks to consider granting them access. The presence of private meetings and the exclusive access to top executives generate an unlevel playing field for investors.

In 2000, the SEC issued Reg FD, which mandates that, when a firm intentionally discloses material information, it must do so through broad public means. If a firm unintentionally discloses material information, it must follow up and publicly disclose the information within twenty-four hours. However, Reg FD has so far posed little threat to private meetings (Bengtzen 2017; Park and Soltes 2018). Regulators do not observe when and with whom such private meetings occur. None of the value-relevant *soft information* sourced during private meetings qualifies as material or intentional disclosure. Even for *hard information*, the threshold of what constitutes material information is extremely high.[3] Since the enactment of Reg FD, the SEC has conducted only five Reg FD enforcement actions against private meetings (Parker and Soltes 2018). Across the five enforcement actions, the highest penalty given to a CEO/CFO was $50,000 and top executives generally have indemnification arrangements that shield them from paying such penalties out of personal funds (Bengtzen 2017). In the end, despite the prevalence of private meetings, the

[3] For instance, during a private dinner meeting between investors and the CFO of Siebel Systems, the CFO revealed that "*new deals were coming into the sales pipeline*" and that "*the company's sales pipeline was growing.*" Participants in the private meeting purchased shares and, the next day, Siebel's stock priced rose by 8% under heavy trading volume. The SEC subsequently sued Siebel Systems for violating Reg FD. Yet, the court quickly dismissed the case as it did not consider the leaked information to be sufficiently material.

likelihood that executives and firms witness Reg FD enforcement action against a private meeting is negligible; even when such an enforcement action occurs, the associated penalty is trivial.

3.1.2 Emergence of Social Executives and Democratization of Access to Top Executives

Starting in 2008, CEOs and CFOs in the largest publicly traded American companies have begun to directly, personally, and, in real-time, connect with investors through Facebook and Twitter. Twitter is the more widely adopted medium. For this reason and for data considerations discussed in Section 4, we focus our analysis on Twitter. Unlike private meetings, any investor can access a top executive's Twitter account.

For our purposes we identify three types of top executives' personal tweets: CEOs and CFOs use their personal Twitter accounts to (1) break company news, (2) describe their work-related day-to-day activities, and (3) share unrelated-to-work personal interests and moods. In this paper, we speculate that some of the hard information that executives share with institutional investors during private meetings may also become reflected in personal tweets of the first type. In addition, if an executive and the corresponding firm do not consider such information sufficiently material, the release of such information may not be accompanied by a public press release or regulatory filing.

More importantly, we observe in our data much variation in the sentiments expressed in tweets of the second and third types.[4] We conjecture that some of the soft information that investors derive from conversations in private meetings (based on a top executive's tone and body language and the executive's response to broad questions such as "What keeps you up at night?") also becomes reflected in tweets describing work-related day-to-day activities. Even tweets

[4] The mean and standard deviation of the fraction of negative words in tweets of the second type are 1.16% and 2.16%; the mean and standard deviation for tweets of the third type are 1.14% and 2.05%, respectively.

describing personal interests and moods may provide useful information to investors, as any positive or negative development at work likely carries over to a top executive's personal life.

Clearly, the presence of social executives is no substitute to private meetings with top executives as a means of staying informed. Still, the emergence of social executives represents a democratization of access to unique and value-relevant information to which, prior to the emergence of social executive, most investors had no access. We therefore hypothesize that the emergence of social executives has helped create a more level playing field.

Based on the market microstructure literature, a more level playing field translates into lower bid–ask spreads, greater depth, and greater trading volume. A more level playing field should also encourage greater investor participation, in particular on the part of retail investors.

Prediction ("Leveling the Playing Field"): The emergence of social executives, by leveling the playing field, improves stock market liquidity and increases a firm's retail investor base.

3.2 Grabbing Investor Attention

3.2.1 Limited Investor Attention

There are well over 4,000 stocks investors can buy (Doidge et al. 2017). In addition, there are more than 18,000 funds to which investors can allocate money (Investment Company Fact Book 2017). It should thus be unsurprising that a large body of research finds evidence that many investors consider only stocks that exhibit salient attributes that grab their attention (e.g., Hirshleifer 2001). If such salient attributes are tied to a firm's fundamentals, the salient-attribute approach may serve investors well. If not, salient attributes may lead to suboptimal investment decisions and suboptimal financial market outcomes.

A key ingredient of the investor attention framework is that those investors who are most decisively affected by salient attributes are thought to be retail investors, not well-informed large institutional investors (e.g., Grullon et al. 2004, Barber and Odean 2008). Moreover, the salient attributes that grab retail investors' attention are typically not related to a firm's fundamentals. Even those that are related to a firm's fundamentals are typically already incorporated into a stock's current price. As a result, the trades induced by attention-generating events and the investors placing those trades "may be best characterized as uninformed trades and . . . uninformed traders" (p. 439–440, Grullon et al., 2004; Barber and Odean, 2008), respectively.

3.2.2 Social Executives Grabbing Investor Attention

In this paper, we propose that the emergence of social executives may have created another salient attribute. The average social executive has 54,978 followers; the average top executive tweet is re-tweeted 389 times. It thus appears plausible that social executives provide entertainment value and grab the attention of retail investors. Unlike in our "Leveling the Playing Field" theory, top executive tweets need not provide unique and value-relevant information to investors.

If the presence of social executives grabs the attention primarily of retail investors, we should observe the number of retail investors rise after a top executive becomes social. In addition, since greater participation on the part of relatively uninformed investors lowers the risk of trading against informationally superior investors, we should also observe stock market liquidity improve in the form of narrower bid–ask spreads, greater depth, and higher trading volumes.

Prediction ("Grabbing Investor Attention"): The emergence of social executives, by attracting retail investor attention, improves stock market liquidity and increases a firm's retail investor base.

4. DATA

4.1 Top Executives' Personal Twitter Accounts

Twitter is a social media outlet that allows a user to post short messages to a network of followers. These short messages are referred to as microblogs or, more commonly, tweets. Followers can choose to follow or unfollow a public Twitter account without the explicit consent of that user. Twitter was founded in 2006 and has since become the most popular microblogging site in the United States. As of December 2014, the end of our sample period, Twitter had some 284 million active users who posted approximately 500 million tweets each day (https://about.twitter.com/company).

To construct our sample of top executives' personal Twitter accounts, we download a list of all CEOs and CFOs in the Execucomp database from 2006 through 2014. The Execucomp database contains compensation data for all top executives of S&P 1500 companies as well as companies that were once part of the S&P 1500 index and that are still trading. We start with the complete list of all CEOs/CFOs in Execucomp and locate users with active Twitter accounts that have the same first and last names as the CEOs/CFOs in question. We then cross-check the executives' middle names, gender, and company information with user characteristics; we also read tweets to determine whether any account that we find does indeed belong to the executive in question.[5] Through this labor-intensive process, we determine that 155 S&P 1500 CEOs/CFOs have active personal Twitter accounts and work for firms that have the data necessary to conduct our tests. We make the full list of the 155 CEOs/CFOs in our sample available on our website.

[5] We acknowledge the possibility that an executive's personal Twitter account may be managed by an executive's assistant or the firm's social media team; we do not have inside information on who is actually posting the tweets or managing the account for a social executive.

We download the following information on each of the 155 social executives through Twitter's API (https://developer.twitter.com/): account identifier ("screen name" in Twitter terms), personal biography, date of account registration, and number of followers as of December 2014. We also download each tweet sent by these 155 social executives over our 2008–2014 sample period. The information that we collect about each tweet includes account identifier, tweet identifier, date, time, content of the tweet, and number of re-tweets.

4.1.1 Descriptive Statistics on Top Executives' Twitter Activity

Table 1 presents descriptive statistics on our final Twitter sample. In 2008, there were only five tweeting executives and they sent a total of 68 tweets. In 2014, 97 tweeting executives sent a total of 11,440 tweets. That is, both the number of executives active on Twitter and the number of tweets sent per executive have increased dramatically over time. The number of active executives in a given year does not reach the 155 figure because some executives post tweets only sporadically.

In Panel C of Table 1 we separate the number of executives and their tweets by four-digit-Global Industry Classification Standard (GICS) industry. Our sample includes tweets from 23 industries. Much activity comes from the "Software & Services" industry. However, we also observe meaningful activity in the "Consumer Services," "Media," "Retailing," and "Technology Hardware & Equipment" industries. In Panels D and E we provide additional information. We have 117 CEOs and 38 CFOs in our sample. CEOs tend to be more active on Twitter than CFOs, with the former sending an average of 387 tweets and the latter sending an average of 68 tweets. Of the 155 executives, 142 are male and 13 are female.

Figure 1 presents a few sample tweets. Some tweets can be construed as representing company-related news announcements, hereafter referred to as "Type 1" tweets. An example of such a tweet is "*Relaunched our Expedia app now with flights and hotel. Beautiful and intuitive:*

Lmk what you think: http:/t.co/IT15MooF" (a tweet sent on 11/14/2012 by Dara Khosrowshahi, CEO of Expedia).

The vast majority of tweets, however, pertain to an executive's day-to-day activities, current set of interests, or mood. As noted in the hypothesis development section, some of these tweets are work-related, hereafter referred to as "Type 2" tweets: "*Earnings call. T-1 hr away. I enjoy taking a step back from the day to day and reflecting on all we have accomplished over the past qtr*" (a tweet sent on 10/29/2009 by John Heyman, CEO of Radiant Systems), or "*More depressed/upset than you've been in years? Try running an airline! – Dave Barger/CEO JetBlue*" (a tweet sent on 12/4/2012 by David Barger, CEO of JetBlue Airways).

Other tweets are clearly not work-related and describe a top executive's personal interests and moods. We hereafter refer to these tweets as "Type 3" tweets: "*Dinner at Hammersley's in Boston—this is still a great restaurant!!*" (a tweet sent on 10/23/2008 by George F. Colony, CEO of Forrester Research), or "*Heading to the @AAarena for the BIG @MiamiHEAT OKC Thunder match-up. Tip is 8pm sharp be there loud & in Black.*" (a tweet sent on 4/4/2012 by Micky Arison, CEO of Carnival).

To compare the effects of the three types of tweets, we present Figure 1 to research assistants (RAs) and ask them to classify each tweet into one of the three types. Each tweet is first read by three RAs. We categorize a tweet into the type into which at least two RAs categorize it. When all three RAs disagree, we have the tweet read by a fourth RA to break the tie. The distribution of tweets across the three types are 4.68%, 49.24%, and 46.08% for Type 1, Type 2, and Type 3 tweets, respectively.

4.1.2 Firm-Managed Twitter Accounts and Facebook

Jung et al. (2017) report that, as of 2015, almost half of all S&P 1500 firms have firm-managed Twitter accounts. Most firm-managed Twitter accounts contain primarily hyperlinks to public press releases (e.g., "Link to $AA 1Q 2012 press release: http://t.co/CdMy5u3O"). Blankespoor et al. (2014) and Jung et al. (2017) examine whether pointing investors to public press releases through Twitter draws additional attention to the corresponding press releases and, if so, how this affects a firm's decision to send such tweets.

While the information broadcast through firm-managed Twitter accounts differs fundamentally from the information transmitted through top executives' personal Twitter accounts, we nevertheless control for firm-managed Twitter accounts in our analysis. For each firm in our sample, we check whether the firm has an official, firm-managed Twitter account. We then re-run our scraping program on these firm-managed Twitter accounts. We find that 140 out of 155 social executives work for firms that have firm-managed Twitter accounts. In 32 out of these 140 cases, it is a top executive who first adopts Twitter; in the remaining 108 cases, a top executive becomes social only after his/her firm has already set up a firm-managed Twitter account.

Facebook serves as an alternative, less popular social media channel through which executives communicate with investors and customers. The vast majority of Twitter accounts are set to be public so that anyone who wishes to follow them can do so without the explicit consent of the Twitter account holder. This setting is less common among Facebook account holders, and Facebook posts are generally observable only to "friends." When we sent friend requests to the 72 CEOs and CFOs whom we identify as having Facebook accounts, only five (6.9%) accepted our friend request. We therefore exclude messages posted on Facebook from our analysis.

4.2 Stock Market Liquidity and Firms' Investor Bases

Our stock market liquidity measures are based on the Trade and Quote (TAQ) database. The TAQ database contains all intraday trades and all intraday bid and ask quotes for almost all stocks traded in the United States. By the final year of our sample period, the trades file contains 24 million rows for each trading day; the quote file contains 550 million rows for each trading day. Processing these files, even for our seemingly short six-year sample period, is therefore highly challenging and requires high-performance computing and advanced big-data techniques.

Our stock market liquidity variables are computed in accordance with those used in prior literature (Holden and Jacobsen 2014). To construct *Percent Effective Spread*, hereafter simply referred to as "*Spread*," we compute, on each day *t* for each firm *i*, for each quote that is matched with a trade, the difference between the ask price and the bid price divided by the lagged midpoint of the ask price and the bid price. We then calculate, for each day *t* and each firm *i*, the equal-weighted average. In our tables and analyses, we express *Spread* in percentage points.

To compute *Average Best-Bid-and-Ask Depth*, hereafter referred to simply as "*Depth*," we compute, for each quote that is matched with a trade, the dollar amount available to trade at the best ask quote plus the dollar amount available to trade at the best bid quote. We then calculate, for each day *t* and each firm *i*, the equal-weighted average. As the *Depth* variable is highly skewed, we take the natural logarithm of *Depth* in our regression analysis to increase model fit.

Turnover is the number of shares traded on a given day divided by the number of shares outstanding. *Turnover* computes the fraction of total shares outstanding that are traded on a given day. In our tables and analyses, we express *Turnover* in percentage points.

We obtain data on the total number of shareholders from COMPUSTAT and data on the number of institutional shareholders from the Thomson Reuters S34 Master file. We construct the

following variables: *#Inst. Investors*, which is the number of institutional investors, and *#Retail Investors*, which is the total number of shareholders minus the number of institutional investors. Institutional investors include banks, insurance companies, mutual funds, pension funds, university endowments and other forms of professional investment advisors. To help interpret the magnitude of the coefficient estimates, the *#Retail Investors* variable is expressed in thousands. We take the natural logarithm of *#Retail Investors* and *#Inst. Investors* in our regression analysis since these variables are highly right skewed.

4.3 Other Variables

In our analysis, we also use earnings data, financial-statement data, and financial-market data from IBES, COMPUSTAT, and CRSP, respectively, to construct controls as described in Figure 2. We also include a measure of an executive's degree of extraversion as measured by his/her speech pattern during interviews (Green et al. 2017)[6] and we compute various executive characteristics using data from the Execucomp database (also described in Figure 2).[7]

To assess whether information transmitted through tweets is distinct from news announcements, we control for news transmitted through the Dow Jones News Service (DJNS) and opinions transmitted through Seeking Alpha (SA). The DJNS publishes more than 19,000 daily news items, including items from *The Wall Street Journal* and *Barron's*.[8] We access DJNS

[6] Green et al. (2017) consider the Q&A sections of earnings conference calls and try to infer an executive's level of extraversion from the statements made by the executive during such conference calls. "*In particular, linguistic research suggests that extraverts have a higher verbal output, use less formal langue, exhibit less word variety, and use more assertive language*." They "*also use more positive and negative emotion words*." (page 2). Green et al. provide a detailed account of their exact methodology in their Online Appendix. The authors find that their measure is fairly persistent at the executive level. The authors thus treat extraversion as a time-invariant manager fixed effect and, for each executive, produce one extraversion score.

[7] Table 2 provides descriptive statistics for some of our controls for both firms with social executives (Panel A) and the full Execucomp sample (Panel B). We find that the medians and various percentiles of key firm characteristics are not materially different between firms with social executives and those in the full Execucomp sample.

[8] https://www.dowjones.com/products/newswires/.

articles for the stocks in our sample via the Factiva database. The *DJNS Articles* variable counts the number of DJNS articles written on firm *i* on day *t*.

SA is a leading social-media platform that provides crowd-sourced equity research articles in the United States. Over our 2008–2014 sample period, SA articles and commentaries are written by approximately 6,000 and 180,000 users, respectively, and cover more than 6,000 firms. We download all single-stock opinion articles that were published from 2008 through 2014 on the SA website and all commentaries written in response to those opinion articles. Our *SeekingAlpha Articles* and *SeekingAlpha Comments* variables count the number of SA articles written on firm *i* on day *t* and the number of SA comments posted about firm *i* on day *t*, respectively. Prior literature provides evidence that both DJNS articles and SA articles/commentaries have high informational value and therefore should serve as meaningful controls (Tetlock 2007; Tetlock et al. 2008; Chen et al. 2014).

5. DETERMINANTS OF TWITTER ADOPTION

Before proceeding to our main tests, we pause to assess what determines a top executive's decision to become social. The results reported in this section provide useful descriptive statistics; they later also help us address endogeneity concerns.

We first assemble the population of all S&P 1500 CEOs and CFOs as per the Execucomp database as of 2007. We then include a host of observable executive- and firm-specific variables as of 2007 and estimate a Probit model to predict a top executive's decision to adopt Twitter over our 2008–2014 sample period.

Our dependent variable equals one if an executive activates a Twitter account during the period that runs from 2008 through 2014 and zero otherwise. The independent variables are: *Executive Age*, *Tenure*, *Male Executive*, *CEO*, *Log(Total Compensation)*, *Extravert*, *Size*, *Book-*

to-Market, *Cash Flow*, *ROA*, *Leverage*, *Dividend*, *Capital Expenditures*, *R&D*, *Sales/Total Assets*, *Sales Growth*, *Loss*, *Tax*, *Log(Firm Age)*, *Spread*, *ΔSpread*, *Log(Depth)*, *ΔLog(Depth)*, *Turnover*, and *ΔTurnover*. All variables are defined in Figure 2. To control for unobservable industry characteristics, we include industry fixed effects.

The results of the Probit model analysis are reported in Column (1) of Table 3. The coefficient estimates indicate that executives who are CEOs, executives who are more extraverted, and executives whose firms have higher returns on assets, higher tax expenses, and greater depth are more likely to adopt Twitter. By contrast, executives who are male, have longer tenure and higher compensation levels, and whose firms have higher cash flows are less likely to adopt Twitter as a platform.

In our main analysis, we use the Heckman correction procedure (Heckman 1979) to account for any potential selection bias that arises from the non-random adoption of Twitter by top executives. In particular, we include the IMR measured at the annual level to address omitted-variable bias concerns due to self-selection. To obtain the annual IMR measure for each executive/year in the S&P 1500 population, we re-estimate the Twitter-adoption prediction model from Column (1) of Table 3 by regressing the Twitter adoption statuses from 2008 through 2014 on independent variables measured from 2007 through 2013. For each executive/year, we then calculate the ratio of the probability density function to the cumulative distribution function to gauge the likelihood that an executive adopts Twitter in a given year.

6. THE EMERGENCE OF SOCIAL EXECUTIVES AND ITS EFFECT ON STOCK MARKET LIQUIDITY AND INVESTOR BASES

6.1 Prelude

Our "Leveling the Playing Field" theory assumes that the presence of social executives imparts unique value-relevant insights. We should thus be able to use executive communication to predict future firm performance. In comparison, under the "Grabbing Investor Attention" theory, executive communication does not predict future fundamentals. Investors nevertheless react to personal tweets as they provide entertainment value and grab investor attention.

To assess the information content in tweets, we build on a large body of literature that examines how information revealed in news articles and blogs relates to future firm performance (e.g., Das and Chen 2007, Tetlock 2007, Tetlock et al. 2008, Chen et al. 2014). In particular, we estimate the following regression equation:

$$Earnings\ Surprises_{i,t+1} = \alpha_t + \beta\ \%Neg\ Tweets_{i,t} + \delta X + \varepsilon_{i,t} \qquad (1)$$

The dependent variable is a measure of earnings surprise and is calculated as the difference between the reported quarterly earnings-per-share (EPS) and the corresponding EPS consensus forecast among professional sell-side analysts as per the IBES database, scaled by the stock price five trading days prior to an earnings announcement. Prior work suggests that the sentiment expressed in a text can be captured by the fraction of negative words in the text (Das and Chen 2007, Tetlock 2007, Tetlock et al. 2008, Chen et al. 2014). Our key independent variable, %*Neg Tweets*, thus is the average fraction of negative words across all tweets posted by a CEO/CFO from the corresponding company's most recent earnings announcement through the day prior to the earnings announcement in question.[9] α_t represent year-month fixed effects. X includes the following control variables: %*Neg DJNS Articles*, *I*(*DJNS Articles*), %*Neg Seeking Alpha Articles*, *I*(*Seeking Alpha Articles*), %*Neg Seeking Alpha Comments*, *I*(*Seeking Alpha Comments*), *Upgrade*, *Downgrade*, *Monthly Volatility*, *Abnormal Returns*$_0$, *Abnormal Returns*$_{-1}$, *Abnormal Returns*$_{-2}$ and

[9] If, for a given firm, both the CEO and CFO are social, we aggregate their personal tweets at the firm level.

Abnormal Returns$_{-60,-3}$. All variables are defined in Figure 2. We cluster our standard errors by firm and year-month.

Consistent with our "Leveling the Playing Field" theory, the regression results shown in Column (1) of Table 4 indicate that views expressed through tweets help predict future earnings surprises. The coefficient estimate for %*Neg Tweets* equals -0.209 (*t*-statistic=-1.99), suggesting that a one-standard-deviation increase in the fraction of negative words (in our earnings surprise analysis sample) lowers future earnings surprises by 0.55%. In Columns (4)–(6) of Table 4 we show that when breaking up the %*Neg Tweets* variable into the fraction of negative words in Type 1 tweets, the fraction of negative words in Type 2 tweets, and the fraction of negative words in Type 3 tweets, respectively, all of the earnings-surprise predictability comes from Type 2 tweets, which are tweets describing an executive's work-related day-to-day activities. Type 3 tweets, which are tweets related to an executive's personal interests and moods, display no predictability. Type 1 tweets, which are company-news announcements, also display no predictability. However, we find in untabulated analysis that when we remove our news-related control variables, %*Neg DJNS Articles*, *I*(*DJNS Articles*), %*Neg Seeking Alpha Articles*, *I*(*Seeking Alpha Articles*), %*Neg Seeking Alpha Comments*, and *I*(*Seeking Alpha Comments*), the coefficient estimate for the fraction of negative words in Type 1 tweets becomes -0.216 (*t*-statistic = -2.28). That is, Type 1 tweets are value-relevant. At the same time, it appears that executives and firms are cautious and, to ensure they are not in potential violation of Reg FD, they accompany Type 1 tweets with public press releases or regulatory filings, which, in turn, are captured by our control variables. Alternatively, firms may want to maximize the impact of the news shared in Type 1 tweets and simultaneously broadcast the news through multiple channels. Either way, the information revealed in Type 1

tweets is not unique and, instead, can be obtained through multiple information dissemination channels.

How do top executives' personal tweets relate to future stock market performance? Under the "Leveling the Playing Field" theory, stock prices should move only in accordance with Type 2 tweets as, based on our previous analysis, Type 2 tweets are the only type that provide unique, value-relevant information. Under the "Grabbing Investor Attention" theory, investors and stock prices may react to any type of tweets as long as they provide entertainment value and attract investor attention. As any price reaction tied to such tweets is not based on fundamentals, prices should subsequently revert (Da et al. 2011).

To assess how stock prices relate to personal tweets, we again draw from prior literature (Tetlock 2007, Chen et al. 2014) and estimate the following regression equation:

$$Abnormal\ Returns_{i,t+m \rightarrow t+n} = \alpha_t + \beta\ \%Neg\ Tweets_{i,t} + \delta X + \varepsilon_{i,t} \qquad (2)$$

The dependent variable is a measure of abnormal stock market performance, where *i* indexes firms and *t* denotes the day on which a tweet is posted. We consider two return windows: the first window runs from *t*+1 through *t*+3 and enables us to examine whether investors react to CEO/CFO tweets; the second window runs from *t*+4 through *t*+5 and helps us address the question whether any initial investor reaction is warranted by fundamentals and permanently moves prices to their new fundamental values or whether any initial investor reaction is subsequently reversed. We compute abnormal returns as the difference between raw returns minus returns on a value-weighted portfolio of firms of similar size, book-to-market ratios, and past returns (Daniel et al. 1997). %*Neg Tweets* is the average fraction of negative words across all tweets posted on day *t* by the CEO/CFO of the company in question.[10] α_t represent year-month fixed effects. We include the same set of

[10] If, for a given firm, both the CEO and the CFO are social, we aggregate their personal tweets at the firm level.

controls as in the earnings-surprise regression, except for the addition of *Pos Earnings Surprise* (*Neg Earnings Surprise*), which equals one if a positive (negative) earnings surprise is announced and zero otherwise. We cluster our standard errors by firm and year-month.

In Column (2) of Table 4 we show that views expressed in tweets predict abnormal stock market performances. In Column (3) of Table 4, we find that the abnormal returns do not revert in the second window from t+4 through t+5. When the dependent variable is *Abnormal Returns*$_{1,3}$, the coefficient estimate for %*Neg Tweets* equals –0.023 (t-statistic=-2.23), suggesting that a one-standard-deviation increase in the fraction of negative words (in our abnormal returns analysis sample) lowers future abnormal returns by 0.06%. As shown in Columns (7)–(9) of Table 4, all of this predictability derives from Type 2 tweets and Type 3 tweets. Moreover, while the price reaction to Type 2 tweets is permanent and does not revert, almost all of the price reaction tied to Type 3 tweets reverts within two trading days (Columns (10)–(12) of Table 4).[11]

In the end, the results reported in this subsection support the assumptions underlying both the "Leveling the Playing Field" theory and the "Grabbing Investor Attention" theory. Personal tweets describing work-related day-to-day activities help predict future operating performance and strongly and permanently move stock prices, consistent with the proposition that such tweets provide unique value-relevant information to investors. Tweets related to an executive's personal interests and moods have no link to a firm's fundamentals. However, consistent with the idea that such tweets provide entertainment value and attract investor attention, we find that the stock market nevertheless reacts to such tweets; any price reaction tied to such tweets subsequently reverses. We now turn to the impact of the emergence of social executives on stock market liquidity and a firm's investor base.

[11] In Column (12) of Table 4, although the coefficient estimate for %*Neg Tweets* is statistically insignificant at the 10% level, it is positive and its magnitude (0.015) is close to the coefficient estimate in Column (9) of Table 4 (-0.017).

6.2 Economic Consequences of the Emergence of Social Executives

Our inferences regarding the economic consequences of executives' Twitter activity are drawn from changes in daily spreads, depth, and turnover around the time a given firm's CEO or CFO becomes social. To tie such changes in our liquidity measures more directly to top executives' becoming social, we conduct a difference-in-differences analysis within a regression framework.[12] In particular, consider an executive employed by treated firm *i* who begins tweeting on day *t*. For each treated firm *i*, we look at the firm's liquidity over the one-year period prior to the top executive's becoming social and we compare it with liquidity over the one-year period following the top executive's becoming social. We exclude executives who adopt Twitter either before they assume the CEO/CFO role or after they leave that role. For firms that have more than one executive adopting Twitter in our sample period, we consider only the first adopting executive.

For each treated firm, we find a control firm through propensity-score matching based on all executive and firm characteristics included in Column (1) of Table 3 (Caliendo and Kopeining 2008; Dehejia and Wahba, 2002; Rosenbaum and Rubin 1983). Our matching results reported in Online Appendix Table 2 suggest that all variables between the treated group and the matched control group are balanced with standardized differences of less than 5%. In Column (2) of Table 3, we also report the results from a Probit regression model that predicts the treatment condition

[12] A key assumption for any difference-in-differences analysis is the parallel-trend assumption. We conduct two tests to validate this assumption in our context. To conserve space, we do not present the results of these analyses in the paper, but, instead, report them in Online Appendix Figure 1 and Table 1. In our first test, we plot the median of our dependent variables (*Spread*, *Log*(*Depth)*, *Turnover*, and *Log(#Retail Investors)*) for both the control and treatment groups over time. We find that the two curves in each of the figures are close to each other prior to the treatment, suggesting that the parallel-trend assumption holds. In our second test, we formally test the parallel-trend assumption within a regression framework and conduct a falsification test on the pre-treatment data by imposing a placebo treatment. For *Spread*, *Log(Depth)*, and *Turnover*, we split the pre-treatment period (12 months) into two halves, and create a dummy *PlaceboAfter*, which equals one for the last six months and zero for the first six months. For *Log(#Retail Investors)*, for which we have three years in the pre-treatment period, *PlaceboAfter* equals one for the last year and zero for the first two years. We then estimate a difference-in-differences model with the interaction term, *Treatment*×*PlaceboAfter*, on our pre-treatment observations. We do not observe a significant placebo treatment effect, suggesting that the dependent variables for the two groups are parallel prior to the treatment. The results remain the same when the pre-treatment period is split at other time points.

on the matched sample of treated and control firms only. All covariates are statistically insignificant at the 10% level, implying that good balance is reached and that our matched control group is observationally identical to the treatment group except for the treatment condition.

While this issue is non-material for our main results,[13] to minimize the effect of potentially confounding factors, in our event window we remove the day the top executive adopts Twitter (or the ensuing day if the executive adopts Twitter on a non-trading day); we also remove the trading days immediately before and after the executive adopts Twitter. To be conservative and further minimize the effect of confounding factors, we remove Twitter adoptions when the day the executive adopts Twitter (or the trading day immediately before and after the executive adopts Twitter) overlaps with the activation of a firm-managed Twitter account, a firm mentioning in the DJNS or SA, or an earnings announcement.[14] As mentioned in Section 4, the DJNS publishes more than 19,000 daily news items; SA publishes more than 5,000 articles a month. Any material firm-related information should thus be captured by our DJNS and SA variables. Our restriction should thus ensure that none of the Twitter adoption events in our difference-in-differences analysis overlaps with material firm-specific news. After imposing all these restrictions and finding matched firms, our final sample includes 128 Twitter adoptions (256 firms in total; 128 treated firms and 128 control firms) and 80,187 firm/day observations.

We estimate the following difference-in-differences regression model:

$$Y_{i,t} = \alpha_i + \delta_t + \beta TreatmentGroup_i \times AfterBecomingSocial_{i,t} + \gamma X + \varepsilon_{i,t} \quad (3)$$

The dependent variable is one of our three liquidity measures, *Spread*, *Log(Depth)*, or *Turnover*. α_i and δ_t are firm and time fixed effects. Firm fixed effects control for any unobservable time-

[13] Without imposing any of the restrictions described in this paragraph, the results are similar to the results presented in the paper and they are available upon request.

[14] In untabulated analyses, we extend the three-day window to longer periods and we observe results similar to those presented in this paper (results available upon request).

invariant firm characteristics. Time fixed effects control for common shocks that affect all firms. Our main variable of interest is the interaction term, *TreatmentGroup×AfterBecomingSocial*. *TreatmentGroup* equals one if firm *i* belongs to the treatment group and zero otherwise. For each treated firm *i* (and its corresponding matched control firm), *AfterBecomingSocial* equals one if the corresponding executive has turned social as of day *t* and zero otherwise. The coefficient estimate for *TreatmentGroup×AfterBecomingSocial* tells us how much a firm's liquidity changes when a top executive becomes social, above and beyond any change experienced by an observationally identical matched firm over the same time frame. Neither *TreatmentGroup* nor *AfterBecomingSocial* is included in our regression model as they are absorbed into the firm and time fixed effects.

X contains the following control variables: We use *I(Presence of Company Twitter Account)*, *#CompanyTweets*, and *Earnings Announcement* to control for firm-initiated disclosures. To control for firm-specific news transmitted through information intermediaries, we include *#DJNS Articles*, *#Seeking Alpha Articles*, *#Seeking Alpha Comments*, *Log(#Analysts)*, and *Inst. Holdings*. Following Blankespoor et al. (2014), we also include |*Abnormal Return*| and *Turnover* to control for any news not captured by our information-intermediaries variables. We do not include the latter variable when our dependent variable is *Turnover*. The market microstructure literature provides evidence that liquidity is higher for large stocks with high stock prices, stocks with low uncertainty, and stocks with many shareholders (Stoll 2000; Holden and Jacobsen 2014).[15] We thus also control for *Size*, *Log(Asset)*, *Log(Price)*, *Monthly Volatility*, *Book-to-Market*, and *Log(#Shareholders)*. Finally, we include *IMR* to control for potential selection bias.

[15] Several cross-country studies provide evidence that differences in the quality of accounting standards affect liquidity (e.g., Eleswarapu and Venkataraman 2006). To the best of our knowledge, there is no well-accepted within-country, across-firm/time measure of quality of accounting standards and we suspect that the quality of accounting standards for our sample firms is fairly homogeneous. The literature also points to seasonality in liquidity (Chordia et al. 2005). Since we conduct a difference-in-differences analysis, those seasonalities will become differenced-out.

For an observation on day *t* in year *y*, we include the *IMR* measure as of the previous year *y*-1 in our model. We cluster our standard errors by both firm and time.

As reported in Column (1) of Table 5, when the dependent variable is a firm's bid–ask spread, our model produces a significant negative coefficient estimate for *TreatmentGroup×AfterBecomingSocial*, -0.024 (*t*-statistic = -4.67), suggesting that when a top executive becomes social, the corresponding firm's bid–ask spread disproportionately decreases by 0.024%. In our sample, the average spread in the month prior to a top executive's becoming social is 0.111%. Our result thus indicates that a top executive's becoming social decreases spreads by 21.6 percentage points (= -0.024%/0.111%).

As shown in Columns (2) and (3), regarding *Log(Depth)*, the coefficient estimate for *TreatmentGroup×AfterBecomingSocial* equals 0.018 (*t*-statistic = 3.63); regarding *Turnover*, the coefficient estimate for *TreatmentGroup×AfterBecomingSocial* equals 0.014 (*t*-statistic = 2.09). The former estimate implies that when a top executive becomes social, the corresponding firm's depth increases approximately by 1.8 percentage points. The latter estimate implies that daily turnover of firms whose top executives start tweeting increase by 0.014%. Considering the average daily turnover in the month prior to a top executive's becoming social, this increase represents a 3.6 percentage points change, or, an additional 0.51 million shares being traded a day.

In Columns (4) and (5) we report results obtained when re-estimating regression equation (3) while replacing the liquidity-based dependent variables with *Log(#Retail Investors)* and *Log(#Inst. Investors)*. Since these variables can be captured only at annual frequency, we now look at the annual number of shareholders over the three-year period prior to a top executive's becoming social and we compare it with the annual number of shareholders over the three-year period following a top executive's becoming social. Our control variables are now also calculated at the

annual frequency and we no longer control for *Inst. Holdings* or *Log(#Shareholders)*. Since we have only a limited number of clusters, we can no longer cluster standard errors by year (Petersen 2009). We can, however, still cluster our standard errors by firm to account for heteroskedasticity and serial correlation. Our final sample includes 1,277 firm/year observations.

In Table 5 we show that, when a top executive becomes social, the corresponding firm experiences a 12.6 percentage points growth in its retail investor base (*t*-statistic = 2.70); for reference, the average number of retail shareholders in our sample is 23,304. In line with our two theories, we observe no association between top executives' becoming social and the number of institutional investors; the coefficient estimate for *TreatmentGroup×AfterBecomingSocial* is -0.014 (*t*-statistic = -0.55).

6.3 Moderating Effects of Twitter Usage

Adopting Twitter is only the first step. How executives use Twitter should play an important role in determining its ultimate economic consequences. To explore how actual Twitter usage affects stock market liquidity and a firm's investor base, we first examine whether our basic patterns are stronger for executives who send more tweets, receive more retweets, or have larger follower bases. We then examine how our main effects vary with Twitter content.

6.3.1 Degree of Twitter Activity

We re-estimate regression equation (3), but we now add a three-way interaction term between *TreatmentGroup×AfterBecomingSocial* and *More#Tweets*, *More#Re-tweets*, and *More#Followers*. *More#Tweets*, *More#Re-tweets*, and *More#Followers* represent indicator variables that equal one if a social executive's average number of tweets per year, re-tweets per year, and total number of followers as of the end of our sample period is above the sample median

and zero otherwise. Each of these three indicators is time-invariant and absorbed into the firm fixed effect. The same applies to the two-way interaction between each moderator and *TreatmentGroup*. However, we can and do add the two-way interaction between each moderator and *AfterBecomingSocial* into our model.

We expect our results to be stronger the more intensely an executive uses his/her personal Twitter account and the wider the executive's follower base is. In line with our expectations, in Table 6 we show that in all regression specifications the results are more pronounced for firms in which (a) the CEO/CFO sends more tweets, (b) tweets are re-tweeted more often, and (c) the Twitter account of the CEO/CFO has more followers. For instance, when the dependent variable is *Spread*, the coefficient estimate for the three-way interaction term *with More#Tweets* is -0.037 (*t*-statistic = -4.74). When the dependent variable is *Log(Depth)*, the estimate becomes 0.034 (*t*-statistic = 4.73). When the dependent variable is *Turnover*, the estimate becomes 0.090 (*t*-statistic = 5.84) and when the dependent variable is *Log(#Retail Investors)*, the estimate becomes 0.132 (*t*-statistic = 1.80). That is, when a social executive posts a great many tweets, the decline in the bid–ask spread and the rises in depth, turnover, and a firm's retail investor base are particularly strong.

6.3.2 Twitter Content

The strength of our effect may vary not only with the intensity with which an executive uses Twitter but also with the content of an executive's tweets. As discussed in Section 4, only 4.68% of tweets represent company news (Type 1) and these tweets do not appear to provide unique value-relevant insights. We therefore now assess whether our liquidity and investor base results are more pronounced for social executives who are more forthcoming when sharing work-related day-to-day activities (Type 2) or for social executives who are more forthcoming when sharing personal interests and moods (Type 3). The results reported in this subsection not only shed light

on the moderating effect of Twitter content but also help us understand which of our two theories best describes our main effects. Based on our "Leveling the playing field" theory, our liquidity and investor base results should be generated by social executives who post primarily work-related tweets. Based on our "Grabbing investor attention" theory, our results should also be present among executives who post primarily unrelated-to-work tweets as these tweets provide entertainment value and grab investor attention.

We re-estimate regression equation (3), but now include a three-way interaction term, *TreatmentGroup*×*AfterBecomingSocial*×*More Work-to-Personal*. *More Work-to-Personal* is an indicator that equals one if the CEO/CFO's (*Work* - *Personal*) / (*Work* + *Personal)* is above the sample median, and zero otherwise, where *Work* (*Personal*) is the number of tweets posted by social executive *i* that are work-related (unrelated-to-work).

As reported in Table 7, in all regression specifications the results are stronger for firms in which the CEO/CFO sends more work-related tweets. In particular, when the dependent variable is *Spread*, the coefficient estimate for the interaction term *TreatmentGroup*× *AfterBecomingSocial*×*More Work-to-Personal* is -0.082 (*t*-statistic = -6.93). When the dependent variable is *Log(Depth)*, the estimate becomes 0.118 (*t*-statistic = 7.72). When the dependent variable is *Turnover*, the estimate becomes 0.144 (*t*-statistic = 6.19) and when the dependent variable is *Log(#Retail Investors)*, the estimate becomes 0.077 (*t*-statistic = 1.51).[16]

7. CAUSAL INFERENCES BASED ON THE SEC'S "EMBRACE OF SOCIAL MEDIA"

[16] The results presented in Table 7 support our "Leveling the playing field" theory. To further gauge the relevance of this theory, we assess whether our results are stronger in cases where, due to the presence of private meetings, the playing field is particularly unlevel prior to the emergence of social executives. Researchers argue and provide corroborating evidence indicating that the benefit from attending private meetings is particularly high when the corresponding firm is a small firm, a growth firm, or a firm with high stock return volatility, as there is less public information available on such firms (Green et al. 2014a; 2014b). If, as a result, the playing field prior to the emergence of social executives is particularly uneven for such firms, we may expect to see the strongest effects among social media adoptions of executives of small firms, growth firms, and firms with high stock return volatility. The results presented in Online Appendix Table 3 strongly corroborate this expectation.

All of the results we have reported so far are consistent with the notion that social media adoptions by top executives help level the playing field. Perhaps to a lesser degree, our results are also consistent with social executives' grabbing investor attention. Despite our difference-in-differences framework and the use of the Heckman correction procedure, there remains the possibility that our results are less a function of top executives' adopting Twitter per se than of some unobservable variable. For instance, a top executive's decision to become social may reflect a change in a firm's overall strategy or a shift in branding efforts. In addition, top executives communicating through social media may be people who, in general, simply have charisma or great allure, which, in turn, translates to greater investor base and stock market liquidity.

Our final analysis utilizes an exogenous shock to top executives' Twitter usage, in particular the SEC's decision, announced on April 2, 2013, to "embrace social media." The results reported in this final section help address endogeneity concerns. They also help further differentiate our "Leveling the playing field" theory from our "Grabbing investor attention" theory.

Until April 2, 2013 it was unclear whether executives posting company-related information on social media accounts were acting in line with Reg FD. On July 5, 2012 Reed Hastings, the CEO of Netflix, announced on his Facebook account that Netflix customers were viewing more than 1 billion hours of video content per month. The Facebook post was widely discussed in the media and accompanied by a 10% stock price increase. The information that Netflix customers were viewing more than 1 billion hours of video content per month was neither disclosed in a press release nor reported in an SEC filing, prompting the SEC to investigate whether the executive was in violation of Reg FD. On April 2, 2013 the SEC announced that it would not press charges against Hastings. The SEC also noted that, in the future, companies and executives could announce

company news exclusively through social media as long as the social media outlet is not restricted and as long as investors are aware that news may be transmitted via social media.

Even though executives had been posting tweets describing their work-related day-to-day activities prior to the SEC's clarification, we conjecture that, since this clarification, executives have felt more comfortable transmitting work-related information through their personal Twitter accounts and, as a result, share more of their work-related day-to-day activities with their followers. To test this hypothesis, we consider firms that employ a social executive as of April 2013. We utilize our manually coded data indicating whether a tweet is work-related (i.e., Type 1 or 2) or not work-related (i.e., Type 3). For each year-month around the SEC's clarification, we compute the fraction of tweets that are work-related. To remove seasonality in tweet type (e.g., there are fewer work-related tweets in the summer), we also calculate, for our full sample, the average fraction of work-related tweets for each of the twelve months, to which we refer hereafter as the "seasonal fraction." The abnormal fraction of work-related tweets in a given year-month is the fraction of work-related tweets in that year-month minus the corresponding seasonal fraction.

Figure 3 plots the abnormal fraction of work-related tweets around the SEC's April 2013 announcement. Consistent with our hypothesis, Figure 3 shows that the fraction of work-related tweets increases abnormally and substantially after April 2013. For instance, the fraction of work-related tweets increases by 9.49% in May 2013 compared with March 2013. The fraction of tweets considered unrelated to work declines correspondingly. As a reminder, 53.92% of the tweets in our sample are categorized as work-related while 46.08% are not work-related. As shown in Figure 3, the discontinuous jump in the fraction of work-related tweets does not revert.

Our earlier evidence implies that work-related tweets are more informative to investors than unrelated-to-work tweets. If there is a causal link between personal Twitter activity and our

outcome variables via levelling the playing field, firms with social executives should thus experience an incremental drop in their spreads, an incremental rise in their depths, an incremental rise in their trading volume, and an incremental widening of their investor bases around the SEC's clarification.

To test this prediction, we estimate a variant of regression equation (3) for our sample of 84 firms that have social executives as of April 2013 (=treated firms) and their matched firms. Matched firms are constructed as in Section 6.2.

The new regression equation is as follows:

$$Y_{i,t} = \alpha_i + \delta_t + \beta TreatmentGroup_i \times PostSECEmbrace_t + \gamma X + \varepsilon_{i,t} \ . \qquad (4)$$

TreatmentGroup×*PostSECEmbrace* is our main variable of interest. *TreatmentGroup* equals one if the observation belongs to a firm with a social executive and zero otherwise. *Post SEC Embrace* equals one if the observation falls after April 2, 2013 and zero otherwise. We include both firm and time fixed effects along with the same set of controls as in regression equation (3). Both *TreatmentGroup* and *PostSECEmbrace* are absorbed into the fixed effects.

For the spread, depth, and turnover analyses, which are conducted at daily frequency, we include observations in the one-year period prior to and after April 2, 2013 (i.e., we cover the period that runs from April 2012 through March 2014). For the shareholder analysis, which is conducted at annual frequency, we include observations in the three-year period prior to and after April 2, 2013 (i.e., we cover the period that runs from 2010 through 2015).

In Columns (1)–(3) of Table 8 we show that the coefficient estimates for *TreatmentGroup*×*PostSECEmbrace* are -0.014 (*t*-statistic of -2.20) for the spread analysis, 0.047 (*t*-statistic = 3.43) for the depth analysis, and 0.092 (*t*-statistic = 4.51) for the turnover analysis. That is, firms with social executives experience an incremental drop in their spreads, an

incremental rise in their depths, and an incremental rise in their trading volumes after the SEC's clarification. The results presented in Column (4) of Table 8 indicate that firms with social executives also experience an incremental rise in the number of retail investors. The estimate is 0.401 (*t*-statistic = 2.46). We continue to see no change in the number of institutional investors.

In summary, our subsample analysis on existing Twitter adopters around a plausibly exogenous shock to Twitter usage yields results that are similar to those reported in Section 6 and indicate a causal relationship between social media adoption by top executives and improved market liquidity and wider investor bases via leveling the playing field.

8. DISCUSSION AND CONCLUSION

Our study is the first to systematically document and describe how top executives have begun to use social media to communicate directly with investors and to examine the economic consequences of this recent development for stock market liquidity. Stock markets are crucial for economic growth (e.g., Levine and Zervos 1998) and stock market liquidity is generally considered the key metric by which a market's quality should be judged (SEC 2015). Here, we provide evidence that the emergence of social executives has helped improve stock market liquidity and widen the investor base. Our evidence based on the SEC's embrace of social media in April 2013 suggests a causal link.

Our study has important practical implications for investors, managers, boards of directors, and regulators. In line with our "Leveling the Playing Field" theory, we find evidence that personal tweets describing work-related day-to-day activities provide useful information to which, prior to the emergence of social executives, most investors would not have had access. The emergence of social executives thus represents an important step towards the democratization of investor access to value-relevant information. The SEC's key objective is to minimize information heterogeneity

and help create "a common pool of knowledge for all investors"[17] as such a common pool is thought to improve market quality and enhance economic growth. Our evidence that social executives can help create such a common pool thus has strong regulatory implications. The relevance of our findings naturally extends to investors who may not yet be aware of the usefulness of top executives' social media accounts, to social executives and executives considering becoming social, and to boards of directors monitoring and advising those executives.

Our study also identifies potential dangers associated with the recent emergence of social executives. We find that tweets describing personal interests and moods that are unrelated to work do not help predict a company's fundamentals. Yet, in line with our "Grabbing Investor Attention" theory, we find evidence that these tweets draw the attention of retail investors and encourage them to invest in and trade shares of firms with social executives. While greater participation by relatively uninformed retail investors may help improve market liquidity and widen the investor base, our results suggest that some retail investors' reactions to tweets that describe top executives' personal interests and moods also destabilize stock prices. Viewed in this light, the SEC's recent embrace of social media, which has encouraged executives to send more work-related tweets and fewer tweets expressing personal interests and moods, represents a positive development for financial markets.

In the end, there is no doubt that "social media is landscape-shifting" (SEC 2012). We hope the results of our study help contribute to a balanced and informed discussion of the impact of the use of social media on financial markets.

[17] https://www.sec.gov/Article/whatwedo.html

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Figure 1. Sample Tweets by Relation to Company's Operations

Tweet	Tweet Date	Screen Name	Executive Name	Industry	Company Name	Type
Very excited about the prospects of the Sirius XM Satellite Radio App due to come out for iPhone users soon!	4/28/2009	MelKarmazin	Mel Karmazin	Media	Sirius XM Holdings	(1) Company news
Western Union launches solution to deliver financial inclusion to millions in #India: prepaid cards.	10/23/2012	WesternUnionCEO	Hikmet Ersek	Software & Services	The Western Union Company	
Relaunched our Expedia app now with flights and hotel. Beautiful and intuitive. Lmk what you think.http:/t.co/IT15MooF	11/14/2012	dkhos	Dara Khosrowshahi	Retailing	Expedia Group	
Just finished a meeting with a lot of good ideas about behavioral mapping ideas	5/7/2009	jmclaughlin173	John P. McLaughlin	Pharma, Biotech & Life Sciences	PDL BioPharma	(2) Work-related day-to-day activities
Earnings call. T- 1 hr away. I enjoy taking a step back from the day to day and reflecting on all we have accomplished over the past qtr.	10/29/2009	johnheyman	John Heyman	Software & Services	Radiant Systems	
More depressed/upset than you've been in years? Try running an airline! -Dave Barger/CEO JetBlue	12/4/2012	DavidJBarger	David Barger	Transportation	JetBlue Airways Corporation	
Dinner at Hammersley's in Boston -this is still a great restaurant!!	10/23/2008	gcolony	George F. Colony	Software & Services	Forrester Research	(3) Unrelated-to-work personal interests and moods
Very disappointed that there will be no season 9 of 24!	3/27/2010	MichaelDell	Michael S. Dell	Technology Hardware & Equipment	Dell	
Heading to the @AAarena for the BIG @MiamiHEAT OKC Thunder match-up. Tip is 8pm sharp be there loud & in Black.	4/4/2012	MickyArison	Micky M. Arison	Consumer Services	Carnival Corporation	

Figure 2. Variable Definitions

Variables	Definitions
Tables 2 and 3	
Size	The firm's market capitalization in millions as of year end
Book-to-Market	The firm's ratio of book value of assets to market value of assets, measured as of the year end and calculated within COMPUSTAT as AT / (AT – CEQ + (#Shares Outstanding[in millions]*Price)
Monthly Volatility	The annual average of standard deviation of the firm's daily stock return in a month
Inst. Holdings	The firm's fraction of shares held by institutional investors as of year end
Price	The firm's close price as of year end
Sales/Total Assets	The firm's revenue per total assets and calculated within COMPUSTAT as REVT/AT
#Retail Investors	The total number of shareholders minus the number of institutional investors, in thousands
#Inst. Investors	The number of institutional investors
Twitter Adoption	An indicator that equals one if an executive activates a Twitter account during the period that runs from 2008 through 2014 and zero otherwise
Executive Age	The executive's age
Tenure	The number of years the executive has been in his/her current CEO/CFO position
Male Executive	An indicator that equals one if the executive is male, and zero otherwise
Extravert	The executive's level of extraversion as reflected by his/her speech pattern during interviews (Green et al. 2016).
Cash Flow	The firm's cash flow and calculated within COMPUSTAT as (OIBDP – XINT – TXT – CAPX) / AT
ROA	The firm's return-on-assets and calculated within COMPUSTAT as OIBDP / AT
Leverage	The firm's debt-to-assets and calculated within COMPUSTAT as (DLC + DLTT) / AT
Dividend	The firm's payout ratio and calculated within COMPUSTAT as DVPSP_F / PRCC_F
Capital Expenditures	The firm's investment in physical assets and calculated within COMPUSTAT as CAPEX / AT
Sales Growth	The firm's annual sales growth rate and calculated within COMPUSTAT as REVT / REVT of the previous year
Loss	An indicator that equals one if a firm has negative net income and zero otherwise
Tax	The effective tax rate and calculated within COMPUSTAT as TXT/EBIT
Log(Firm Age)	The natural logarithm of the number of years the firm has been publicly traded
Spread; *ΔSpread*	The average daily percentage spread in 2007; the change in *Spread* from 2006 to 2007
Turnover; *ΔTurnover*	The average daily turnover in 2007; the change in *Turnover* from 2006 to 2007

Variables	Definitions
Tables 4	
Earnings Surprises	The difference between the reported EPS and the average quarterly EPS forecast using the IBES unadjusted detail-history file, scaled by the stock price five trading days prior to the earnings announcement
Abnormal Returns$_{1,3}$	Cumulative abnormal returns over the three trading days following the date of a tweet. Abnormal returns are the difference between raw returns minus returns on a value-weighted portfolio of firms of similar size, book-to-market ratios, and past returns
Abnormal Returns$_{4,5}$	Cumulative abnormal returns over trading days four through five following the date of a tweet. Abnormal returns are the difference between raw returns minus returns on a value-weighted portfolio of firms of similar size, book-to-market ratios, and past returns
%Neg DJNS Articles	The average fraction of negative words across all articles published in the DJNS about the corresponding firm on day t; this variable is set to zero if there are no DJNS articles
I(DJNS Articles)	An indicator that equals one if there are DJNS articles published about the firm in question, and zero otherwise
%Neg Tweets	The average fraction of negative words across all tweets posted on day t by the CEO/CFO
I(Seeking Alpha Articles)	An indicator that equals one if there are Seeking Alpha articles published about the firm in question, and zero otherwise
%Neg Seeking Alpha Comments	The average fraction of negative words across Seeking Alpha comments posted over day t in response to Seeking Alpha articles about the corresponding firm; this variable is set to zero if there are no Seeking Alpha comments
I(Seeking Alpha Comments)	An indicator that equals one if there are Seeking Alpha comments posted about the firm in question, and zero otherwise
Upgrade	The number of recommendation upgrades for the corresponding firm on day t from the IBES recommendation file
Downgrade	The number of recommendation downgrades for the corresponding firm on day t from the IBES recommendation file
Pos Earnings Surprise	An indicator that equals one if a positive earnings surprise is announced and zero otherwise. We use the IBES unadjusted detail-history file to compute the earnings-surprise measure, which is the difference between the reported EPS and the average quarterly EPS forecast.
Neg Earnings Surprise	An indicator that equals one if a negative earnings surprise is announced and zero otherwise. We use the IBES unadjusted detail-history file to compute the earnings-surprise measure, which is the difference between the reported EPS and the average quarterly EPS forecast.
Monthly Volatility	The standard deviation of the firm's daily stock returns in the calendar month prior to day t
Abnormal Returns$_{0}$	Abnormal returns on day t. Abnormal returns are the difference between raw returns minus returns on a value-weighted portfolio of firms of similar size, book-to-market ratios, and past returns.
Abnormal Returns$_{-1}$	Abnormal returns on day t-1. Abnormal returns are the difference between raw returns minus returns on a value-weighted portfolio of firms of similar size, book-to-market ratios, and past returns.

Variables	Definitions
Abnormal Returns$_{-2}$	Abnormal returns on day t-2. Abnormal returns are the difference between raw returns minus returns on a value-weighted portfolio of firms of similar size, book-to-market ratios, and past returns.
Abnormal Returns$_{-60,-3}$	Cumulative abnormal returns over the three calendar months prior to day t. Abnormal returns are the difference between raw returns minus returns on a value-weighted portfolio of firms of similar size, book-to-market ratios, and past returns.
%Neg Tweets _Type 1	The average fraction of negative words across Type 1 tweets posted on day t by the CEO/CFO
%Neg Tweets _Type 2	The average fraction of negative words across Type 2 tweets posted on day t by the CEO/CFO
%Neg Tweets _Type 3	The average fraction of negative words across Type 3 tweets posted on day t by the CEO/CFO
Tables 5, 6, 7, and 8 (When dependent variable is *Spread*, *Log(Depth)*, *Turnover*, *t* represents days; otherwise, *t* represents years)	
Spread	The daily percentage spread
Log(Depth)	The natural logarithm of the daily depth
Turnover	The daily turnover
#Inst. Investors	The number of institutional investors
#Retail Investors	The total number of shareholders minus the number of institutional investors, in thousands
TreatmentGroup	An indicator that equals one if the corresponding firm belongs to the treatment group and zero otherwise
AfterBecomingSocial	An indicator that equals one if the CEO/CFO has been tweeting as of time t and zero otherwise
I(Presence of Company Twitter Account)	An indicator that equals one if the corresponding firm has a company-managed Twitter account as of time t
#CompanyTweets	The number of tweets posted across all company-managed Twitter accounts at time t by the corresponding firm
#DJNS Articles	The number of articles published in the DJNS about the corresponding firm at time t
%Neg DJNS Articles	The average fraction of negative words across all articles published in the DJNS about the corresponding firm at time t; this variable is set to zero if there are no Seeking Alpha articles
#Seeking Alpha Articles	The number of articles published on Seeking Alpha about the corresponding firm at time t
%Neg Seeking Alpha Articles	The average fraction of negative words across all articles published on Seeking Alpha about the corresponding firm at time t; this variable is set to zero if there are no Seeking Alpha articles
#Seeking Alpha Comments	The number of Seeking Alpha comments posted over time t in response to Seeking Alpha articles about the corresponding firm
%Neg Seeking Alpha Comments	The average fraction of negative words across Seeking Alpha comments posted over time t in response to Seeking Alpha articles about the corresponding firm; this variable is set to zero if there are no Seeking Alpha comments

Variables	Definitions
Earnings Announcement	An indicator that equals one if the corresponding firm announces earnings at time t
Log(#Analysts)	The natural logarithm of 1 plus the number of analysts issuing a forecast in the most recent quarter as captured by I/B/E/S
Inst. Holdings	The corresponding firm's fraction of shares held by institutional investors, measured as of the most recent quarter end
|*Abnormal Return*|	The absolute value of the difference between a firm's cumulative return and the cumulative value-weighted return of all firms in the CRSP sample at time t
Turnover	The daily trading volume divided by the number of shares outstanding
Size	The firm's market capitalization in millions at time t-1
Book-to-Market	The firm's ratio of book value of assets to market value of assets, measured as of the most recent fiscal-quarter end and calculated within COMPUSTAT as ATQ / (ATQ – CEQQ + (#Shares Outstanding[in millions]*Price)
Log(Asset)	The natural logarithm of total assets as of the previous fiscal-quarter end
Log(Price)	The natural logarithm of the firm's close price at time t-1
Monthly Volatility	The standard deviation of corresponding firm's daily stock return in the previous month
Log(#Shareholders)	The natural logarithm of the total number of shareholders as of the most recent fiscal-quarter end
IMR	We re-estimate the Twitter-adoption prediction model using independent variables from 2007 through 2013 and Twitter adoptions from 2008 through 2014. For each executive/year, we then calculate the ratio of the probability density function to the cumulative distribution function to gauge the likelihood that an executive adopts Twitter in a given year.
More #Tweets	An indicator that equals one if the CEO/CFO's average number of tweets per year is above the sample median, and zero otherwise
More #Re-tweets	An indicator that equals one if the CEO/CFO's average number of re-tweets per year is above the sample median, and zero otherwise
More #Followers	An indicator that equals one if the CEO/CFO's total number of followers at the end of our sample period is above the sample median, and zero otherwise
More Work-to-Personal	An indicator that equals one if the CEO/CFO's (*Work* - *Personal*)/(*Work* + *Personal*) is above the sample median, and zero otherwise, where *Work* (*Personal*) is the number of Type 2 tweets (Type 3 tweets) posted by the CEO/CFO
Post SEC Embrace	An indicator that equals one if the observation is after April 2, 2013 and zero otherwise

Figure 3. Monthly Abnormal Fraction of Work-Related Tweets around the "SEC's Embrace of Social Media"

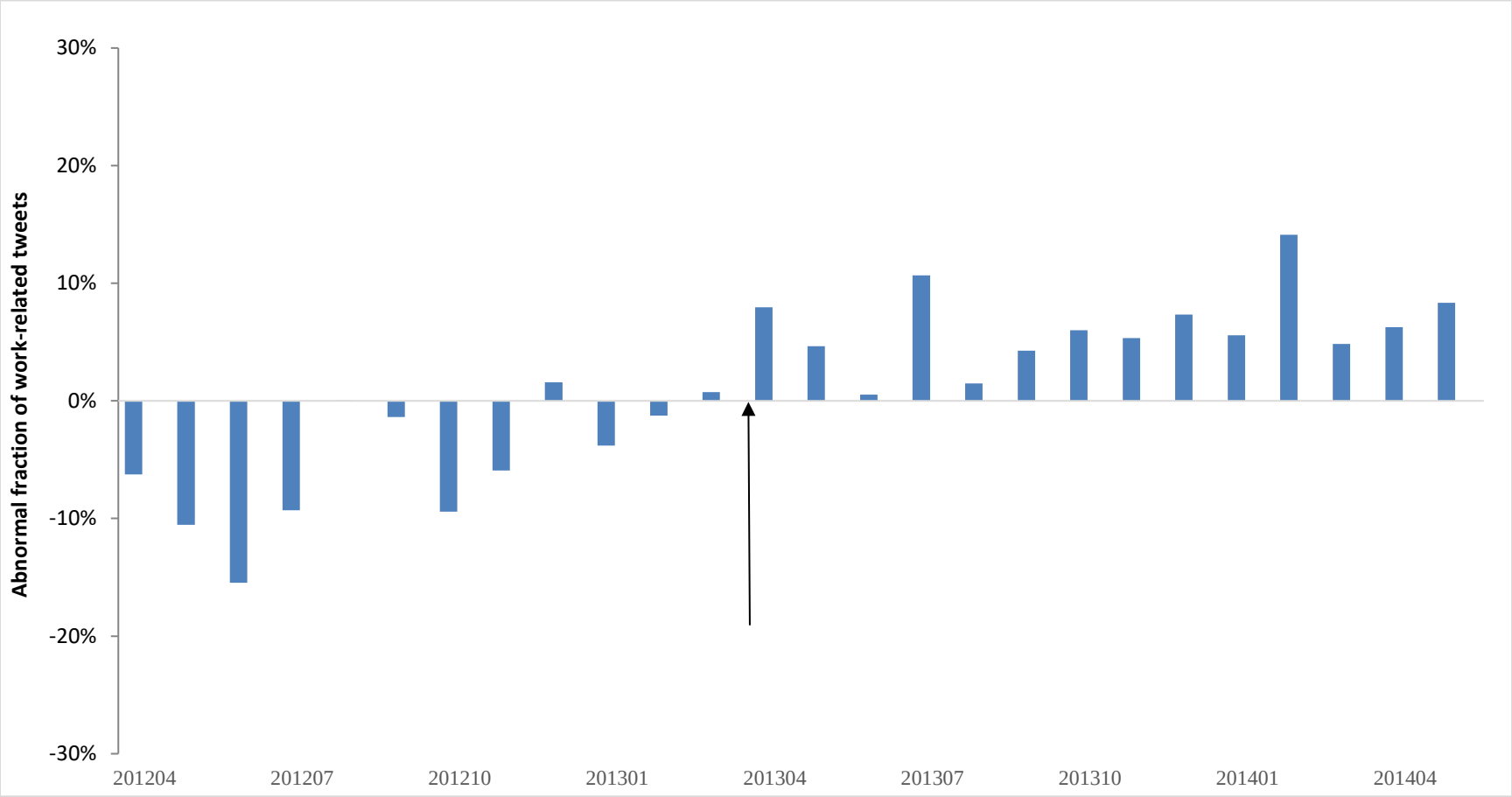

Table 1. Descriptive Statistics on Tweets

	Total #Executives	Total #Firms	Total #Tweets	Total #Tweets per Firm
Panel A: Full Sample				
ALL	155	142	47,119	331.82
Panel B: Calendar Year				
2008	5	5	68	13.60
2009	43	41	2,450	59.76
2010	45	43	3,266	72.95
2011	65	64	7,538	117.78
2012	79	75	12,408	165.44
2013	89	86	9,949	115.69
2014	97	91	11,440	125.71

Table 1. Continued.

	Total #Executives	Total #Firms	Total #Tweets	Total #Tweets per Firm
Panel C: GICS Industry Groups				
Automobiles and Components	1	1	260	260.00
Banks	3	3	345	115.00
Capital Goods	5	4	1,881	470.50
Commercial & Professional Services	7	6	2,191	365.17
Consumer Durables & Apparel	0	0	0	0
Consumer Services	10	10	9,866	986.60
Diversified Financials	4	4	655	163.75
Energy	3	3	91	30.33
Food & Staples Retailing	2	2	334	167.00
Food, Beverage & Tobacco	6	5	1,706	341.20
Health Care Equipment & Services	7	7	2,801	400.14
Household & Personal Products	2	2	2,237	1118.50
Insurance	2	2	34	17.00
Materials	4	4	103	25.75
Media	10	9	2,176	241.78
Pharma, Biotech & Life Sciences	2	2	765	382.50
Real Estate	1	1	30	30.00
Retailing	10	9	2,419	268.78
Semiconductors	6	6	516	86.00
Software & Services	46	38	11,087	292.05
Technology Hardware & Equipment	12	12	5,394	449.50
Telecommunication	5	4	318	79.50
Transportation	2	2	1,567	783.50
Utilities	5	5	343	68.60

Table 1. Continued.

	Total #Executives	Total #Firms	Total #Tweets	Total #Tweets per Firm
Panel D: Executive Type				
CEO	117	116	44,586	386.69
CFO	38	37	2,533	68.46
Panel E: Executive Gender				
Male	142	130	45,233	347.95
Female	13	12	1,886	157.17

Table 2. Descriptive Statistics – Firm/Year Level

	N	Mean	Std. Dev	25th Pctl	50th Pctl	75th Pctl
Panel A: "Tweeting" Firms						
Size	994	17,664	59,255	556	1,395	5,730
Book-to-Market	994	0.61	0.57	0.26	0.48	0.80
Monthly Volatility	994	2.27%	15.02%	0.09%	0.39%	1.30%
Inst. Holdings	994	0.75	0.22	0.63	0.79	0.93
Price	994	263.52	4703.96	11.88	23.91	39.21
Sales/Total Assets	994	1.04	1.05	0.49	0.78	1.23
#Retail Investors	994	17.74	70.80	0.06	1.23	8.54
#Inst. Investors	994	287	339	115	168	326
Panel B: Full Execucomp Sample						
Size	11,652	8,137	25,821	606	1,679	5,159
Book-to-Market	11,652	0.79	3.04	0.31	0.53	0.86
Monthly Volatility	11,652	1.75%	14.33%	0.06%	0.28%	1.06%
Inst. Holdings	11,652	0.77	0.20	0.66	0.80	0.92
Price	11,652	50.70	1,186.75	13.57	26.48	45.25
Sales/Total Assets	11,652	0.93	0.98	0.37	0.74	1.24
#Retail Investors	11,652	27.68	855.07	0.04	1.20	8.36
#Inst. Investors	11,652	260	246	119	176	312
Panel C: DiD Matched Sample						
Size	1,684	14,186	45,567	672	1,890	7,678
Book-to-Market	1,684	0.76	2.10	0.27	0.48	0.79
Monthly Volatility	1,684	1.76%	11.32%	0.06%	0.30%	1.08%
Inst. Holdings	1,684	0.76	0.21	0.65	0.79	0.93
Price	1,684	159.01	3,372.75	13.33	25.91	42.44
Sales/Total Assets	1,684	1.01	0.91	0.48	0.78	1.29
#Retail Investors	1,684	20.49	67.54	0.09	1.34	10.00
#Inst. Investors	1,684	297	306	123	194	363

Table 3. Determinants of Top Executives' Twitter Adoption

	Twitter Adoption (1)	Twitter Adoption (after-match) (2)
Executive Age	0.007	0.007
	(1.25)	(0.39)
Tenure	-0.033***	-0.013
	(-2.77)	(-1.02)
Male Executive	-0.494***	-0.091
	(-3.61)	(-0.50)
CEO	0.767***	0.136
	(6.50)	(0.68)
Log(Total Compensation)	-0.123***	-0.096
	(-3.63)	(-1.30)
Extravert	0.055**	-0.006
	(1.98)	(-0.06)
Size	0.031	-0.022
	(0.85)	(-0.35)
Book-to-Market	0.051	-0.086
	(0.71)	(-0.26)
Cash Flow	-1.638***	-0.963
	(-3.48)	(-0.56)
ROA	1.316***	-0.188
	(3.36)	(-0.11)
Leverage	-0.027	0.682
	(-0.11)	(1.29)
Dividend	22.734	0.036
	(1.00)	(0.08)
Capital Expenditures	-1.680	0.197
	(-1.24)	(0.10)
R&D	0.019	1.795
	(0.02)	(0.79)
Sales/Total Assets	0.038	0.162
	(0.34)	(0.93)
Sales Growth	0.000	1.055
	(0.02)	(1.54)
Loss	-0.255	0.009
	(-1.16)	(0.02)
Tax	0.032***	-0.100
	(2.87)	(-1.52)
Log(Firm Age)	-0.080	0.175
	(-1.27)	(1.58)
Spread	0.283	-0.450
	(1.21)	(-1.08)
ΔSpread	-0.267	-0.081
	(-1.14)	(-0.18)

Table 3. Continued.

	Twitter Adoption (1)	Twitter Adoption (after-match) (2)
Log(Depth)	0.162**	-0.025
	(2.15)	(-0.20)
ΔLog(Depth)	-0.101	0.115
	(-0.97)	(0.33)
Turnover	16.047	-16.216
	(1.37)	(-0.86)
ΔTurnover	10.392	-12.023
	(0.87)	(-0.92)
# Obs.	3,960	256
Adj. R^2	0.216	0.175

Notes: (1) industry fixed effects are included in the regression; (2) t-statistics are computed using standard errors clustered by industry are reported in parentheses; and (3) statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Table 4. Information Content in Top Executives' Tweets

	Earnings Surprises [%]	Abnormal Returns$_{1,3}$	Abnormal Returns$_{4,5}$
	(1)	(2)	(3)
%Neg Tweets	-0.209**	-0.023**	0.012
	(-1.99)	(-2.23)	(1.44)
%Neg DJNS Articles	-0.044	0.032	0.046
	(-0.08)	(0.20)	(0.40)
I(*DJNS Articles*)	-0.001	-0.001	-0.003
	(-0.19)	(-0.22)	(-1.30)
%Neg Seeking Alpha Articles	-0.232	-0.061	0.151
	(-0.87)	(-0.24)	(1.21)
I(*Seeking Alpha Articles*)	0.003	0.003	-0.005*
	(0.62)	(0.71)	(-1.85)
%Neg Seeking Alpha Comments	-0.028	-0.160	-0.043
	(-0.17)	(-1.07)	(-0.63)
I(*Seeking Alpha Comments*)	0.002	0.001	0.005*
	(0.53)	(0.12)	(1.79)
Upgrade	-0.010	0.005*	-0.003
	(-0.52)	(1.84)	(-1.14)
Downgrade	0.015	-0.005	-0.001
	(0.77)	(-1.44)	(-0.35)
Pos Earnings Surprise		0.014***	0.001
		(2.63)	(0.57)
Neg Earnings Surprise		-0.035***	0.004
		(-4.00)	(1.42)
Monthly Volatility	-2.856**	0.065	0.029
	(-2.65)	(1.55)	(1.12)
Abnormal Returns$_{0}$	-0.086	-0.052***	-0.002
	(-0.52)	(-2.67)	(-0.14)
Abnormal Returns$_{-1}$	0.008	-0.023	-0.004
	(-1.02)	(-1.38)	(-0.31)
Abnormal Returns$_{-2}$	-0.806	-0.041**	-0.009
	(-1.02)	(-2.16)	(-0.53)
Abnormal Returns$_{-60,-3}$	0.017	-0.007*	-0.003
	(0.41)	(-1.91)	(-1.16)
# Obs.	12,949	12,949	12,949
Adj. R^2	0.110	0.024	0.011

Table 4. Continued.

	Earnings Surprises [%]	Earnings Surprises [%]	Earnings Surprises [%]	Abnormal $Returns_{1,3}$	Abnormal $Returns_{1,3}$	Abnormal $Returns_{1,3}$	Abnormal $Returns_{4,5}$	Abnormal $Returns_{4,5}$	Abnormal $Returns_{4,5}$
	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
%Neg Tweets _Type 1	-0.022			-0.020			0.003		
	(-0.45)			(-0.31)			(0.57)		
%Neg Tweets _Type 2		-0.435**			-0.033**			0.007	
		(-2.09)			(-1.97)			(0.66)	
%Neg Tweets _Type 3			0.049			-0.017**			0.015
			(0.28)			(-2.40)			(1.24)
Control?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# Obs.	667	6,150	6,132	667	6,150	6,132	667	6,150	6,132
Adj. R^2	0.388	0.048	0.071	0.217	0.041	0.036	0.123	0.027	0.023

Notes: (1) *t*-statistics are computed using standard errors clustered by both firm and time and are reported in parentheses; (2) statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Table 5. The Effects of Twitter Adoption on Liquidity and Shareholder Base

	Spread [%]	Log(Depth)	Turnover [%]	Log(#Retail Investors)	Log(#Inst. Investors)
	(1)	(2)	(3)	(4)	(5)
TreatmentGroup × AfterBecomingSocial	-0.024***	0.018***	0.014**	0.126**	-0.014
	(-4.67)	(3.63)	(2.09)	(2.70)	(-0.55)
I(Presence of Company Twitter Account)	-0.006*	0.043***	0.057*	-0.075	0.070
	(-1.81)	(4.13)	(1.66)	(-1.04)	(1.44)
#Company Tweets	-0.001***	-0.000	0.001	0.000	-0.000
	(-3.99)	(-0.38)	(1.08)	(0.83)	(-1.05)
#DJNS Articles	-0.002	-0.003	0.077***	-0.000	-0.000***
	(-0.31)	(-1.03)	(2.45)	(-0.44)	(-3.98)
%Neg DJNS Articles	0.136	0.330	6.535***	2.019	-0.607
	(0.22)	(0.93)	(3.31)	(1.38)	(-0.59)
#Seeking Alpha Articles	-0.144	0.042	-0.360***	0.011	-0.063
	(-1.17)	(0.64)	(-2.63)	(0.41)	(-0.80)
%Neg Seeking Alpha Articles	5.810	2.536	15.269	-0.805	3.757
	(0.53)	(0.62)	(1.36)	(-0.34)	(0.69)
#Seeking Alpha Comments	0.337*	0.027	0.204*	-0.003	0.031
	(1.74)	(0.39)	(1.71)	(-0.09)	(0.80)
%Neg Seeking Alpha Comments	0.584	-0.897	-1.235	-0.179	-0.316
	(0.06)	(-0.50)	(-0.34)	(-0.11)	(-0.22)
Earnings Announcement	-0.003	-0.051***	0.455***		
	(-0.67)	(-3.78)	(8.80)		
Log(#Analysts)	-0.023***	0.007**	0.029***	-0.139**	0.084**
	(-7.78)	(1.95)	(4.97)	(-2.22)	(2.26)
Inst. Holdings	0.132***	0.279***	0.427***		
	(3.38)	(9.04)	(6.30)		
|Abnormal Return|	-0.059*	-0.197	14.988***	0.061	-0.079***
	(-1.83)	(-1.61)	(12.31)	(1.59)	(-2.96)
Turnover	0.132	5.923***		-0.416	1.748***
	(1.40)	(13.03)		(-0.22)	(3.00)

Table 5. Continued.

	Spread [%]	Log(Depth)	Turnover [%]	Log(#Retail Investors)	Log(#Inst. Investors)
	(1)	(2)	(3)	(4)	(5)
Size	0.115***	0.210***	0.009	-0.049	0.227***
	(3.29)	(6.68)	(0.21)	(-0.33)	(5.58)
Book-to-Market	-0.001	-0.005	-0.018*	0.040**	-0.015
	(-0.71)	(-1.34)	(-1.85)	(2.30)	(-0.93)
Log(Asset)	-0.001	0.123***	-0.016	0.021	0.006
	(-0.09)	(8.49)	(-0.67)	(1.62)	(0.93)
Log(Price)	-0.143***	0.178***	0.131***	-0.090	-0.093***
	(-3.91)	(5.86)	(3.55)	(-0.61)	(-2.48)
Monthly Volatility	-0.034	1.026***	2.437***	1.060	-1.146
	(-0.56)	(3.87)	(3.33)	(0.98)	(-0.84)
Log(#Shareholders)	-0.006*	0.030***	0.007		
	(-1.87)	(4.24)	(0.51)		
IMR	-0.024***	-0.027***	-0.014	0.068	-0.006
	(-7.44)	(-6.04)	(-1.48)	(1.13)	(-0.29)
# Obs.	80,187	80,187	80,187	1,277	1,277
Adj. R^2	0.222	0.931	0.517	0.969	0.946

Notes: (1) firm and time fixed effects are included in the regressions; (2) in Columns (1)-(3), *t*-statistics are computed using standard errors clustered by both firm and time and are reported in parentheses; (3) in Columns (4)-(5), *t*-statistics are computed using standard errors clustered by firm only; and (4) statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Table 6. The Effects of Twitter Adoption on Liquidity and Investor Base: Account Characteristics as a Moderator

	Spread [%]			Log(Depth)			Turnover [%]		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
TreatmentGroup × AfterBecomingSocial	-0.004	0.010	0.021***	-0.029***	-0.014*	-0.055***	-0.063***	0.008	-0.063***
	(-0.63)	(1.34)	(2.49)	(-3.22)	(-1.71)	(-6.71)	(-5.01)	(0.79)	(-4.70)
TreatmentGroup × AfterBecomingSocial × More #Tweets	-0.037***			0.034***			0.090***		
	(-4.74)			(4.73)			(5.84)		
TreatmentGroup × AfterBecomingSocial × More #Re-tweets		-0.059***			0.026***			0.039***	
		(-7.42)			(3.57)			(2.82)	
TreatmentGroup × AfterBecomingSocial × More #Followers			-0.068***			0.054***			0.074***
			(-7.55)			(7.43)			(4.81)
Control?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# Obs.	80,187	80,187	80,187	80,187	80,187	80,187	80,187	80,187	80,187
Adj. R^2	0.222	0.223	0.223	0.931	0.931	0.931	0.517	0.517	0.517

	Log(#Retail Investors)			Log(#Inst. Investors)		
	(10)	(11)	(12)	(13)	(14)	(15)
TreatmentGroup × AfterBecomingSocial	0.048	-0.027	0.071	-0.035	-0.012	-0.013
	(0.26)	(-0.14)	(0.40)	(-1.08)	(-0.36)	(-0.41)
TreatmentGroup × AfterBecomingSocial × More #Tweets	0.132*			0.036		
	(1.80)			(0.84)		
TreatmentGroup × AfterBecomingSocial × More #Re-tweets		0.444***			-0.007	
		(3.88)			(-0.16)	
TreatmentGroup × AfterBecomingSocial × More #Followers			0.203*			-0.006
			(1.71)			(-0.15)
Control?	Yes	Yes	Yes	Yes	Yes	Yes
# Obs.	1,277	1,277	1,277	1,277	1,277	1,277
Adj. R^2	0.914	0.914	0.914	0.946	0.946	0.946

Notes: (1) firm and time fixed effects are included in the regressions; (2) in Columns (1)-(9), *t*-statistics are computed using standard errors clustered by both firm and time and are reported in parentheses; (3) in Columns (10)-(15), *t*-statistics are computed using standard errors clustered by firm only; and (4) statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Table 7. The Effects of Twitter Adoption on Liquidity and Investor Base: Twitter Content as a Moderator

	Spread [%]	Log(Depth)	Turnover [%]	Log(#Retail Investors)	Log(#Inst. Investors)
	(1)	(2)	(3)	(4)	(5)
TreatmentGroup × AfterBecomingSocial	-0.016***	0.006	0.029***	0.076	0.050
	(-3.09)	(1.16)	(3.14)	(0.69)	(0.99)
TreatmentGroup × AfterBecomingSocial × More Work-to-personal	-0.082***	0.118***	0.144***	0.077	-0.059
	(-6.93)	(7.72)	(6.19)	(1.51)	(-0.38)
Control?	Yes	Yes	Yes	Yes	Yes
# Obs.	80,187	80,187	80,187	1,277	1,277
Adj. R^2	0.222	0.931	0.517	0.914	0.946

Notes: (1) firm and time fixed effects are included in the regressions; (2) in Columns (1)-(3), *t*-statistics are computed using standard errors clustered by both firm and time and are reported in parentheses; (3) in Columns (4)-(5), *t*-statistics are computed using standard errors clustered by firm only; and (4) statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Table 8. The Effect of the SEC's Embrace of Social Media

	Spread [%]	Log(Depth)	Turnover [%]	Log(#Retail Investors)	Log(#Inst. Investors)
	(1)	(2)	(3)	(4)	(5)
TreatmentGroup × PostSECEmbrace	-0.014**	0.047***	0.092***	0.401**	-0.170
	(-2.20)	(3.43)	(4.51)	(2.46)	(-1.46)
Control?	Yes	Yes	Yes	Yes	Yes
# Obs.	23,851	23,851	23,851	1,003	1,003
Adj. R^2	0.220	0.942	0.509	0.904	0.940

Notes: (1) firm and time fixed effects are included in the regressions; (2) in Columns (1)-(3), *t*-statistics are computed using standard errors clustered by both firm and time and are reported in parentheses; (3) in Columns (4)-(5), *t*-statistics are computed using standard errors clustered by firm only; and (4) statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.