THE EMERGENCE OF "SOCIAL EXECUTIVES" AND ITS CONSEQUENCES FOR FINANCIAL MARKETS

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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, and we conjecture that this increases retail investor participation and improves 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 hypothesis. 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.

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1. INTRODUCTION

Over the past decade, social media has begun to fundamentally alter the manner in which firms broadcast news and investors discuss and form opinions on stocks and asset classes. Jung et al. (2018), for instance, report that, as of 2015, almost half of all S&P 1500 firms have firm-managed Twitter accounts, which they use to draw investors' attention to public press releases (e.g., "Link to $AA 1Q 2012 press release: http://t.co/CdMy5u3O"). Chen et al. (2014) note that investors increasingly inform each other through social media and, along with Jame et al. (2016), they provide evidence that opinions formed on investment-related social-media websites help predict future earnings and stock returns. Heimer (2016) finds evidence that once investors "befriend" one another on social media, their trading patterns become more correlated.

Our purpose in this paper is to provide fresh perspectives on how social media is continuously and importantly changing the manner in which financial market participants interact with one another and to provide evidence on how, ultimately, these changes are affecting financial markets. In particular, we note that over the past decade, there has been a sizeable shift in the way CEOs and CFOs communicate with investors as some CEOs and CFOs have begun to connect with investors directly, personally, and in real time through social media outlets, of which Twitter is the most widely adopted social media platform. We hereafter refer to these executives as "social executives."

We observe that while in 2008, our sample comprises only five CEOs and CFOs sending a total of 68 tweets, by the end of our sample period in 2014, our sample grows to 155 social executives posting a total of 47,119 tweets and whose firms make up roughly 14% of the total United States (U.S.) stock market capitalization. Across all the Global Industry Classification Standard (GICS) industry groups, there are social executives in all but one GICS industry group. In terms of content, we find that 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.

We conjecture that the emergence of social executives has important ramifications for financial markets. CEOs and CFOs probably possess the most comprehensive information about how a company is performing. They are also the key decision makers in a company. It should thus not surprise that investors yearn to hear from top executives and unearth some of the inside perspectives that these executives possess (Bengtzen 2017).

Much of such top executive/investor communication happens in the form of "private meetings" (Soltes 2014). Private meetings are one-on-one meetings between firm representatives and investors; they 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. 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.

Prior literature notes that 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). The presence of private meetings and the unequal access to them create an uneven playing field among investors.

In our paper, we make two predictions. First, we speculate that investors are able to catch a unique glimpse of how a company is performing based on what a CEO or CFO is willing to share via social media. We refer to this possibility as the *value-relevance of executive tweets hypothesis*.

Second, to the degree that our *value-relevance of executive tweets hypothesis* holds true, we argue that since any investor can freely follow any public Twitter account, the emergence of social executives marks a democratization of investor access to top executives for unique and value-relevant information. The presence of social executives is clearly no substitute to private meetings and a significant amount of information heterogeneity among investors remains. Still, the emergence of social executives enables retail investors to obtain value-relevant information from top executives to which they previously had no access, thereby, possibly, turning the playing field across retail and institutional investors comparatively more level.

A long line of work in the finance literature, also known as market microstructure theory, shows that a more level playing field among investors has important economic consequences for financial markets by improving stock market liquidity and investor participation. The reason is that in the presence of investors with valuable private information, the remaining investor population cannot be confident that any stock transaction occurs at a "fair price." The remaining investor population thus is reluctant to trade, and stock market liquidity dries up. As the playing field among investors becomes more level the risk of trading against informationally superior investors declines, stock market participation of the previously more disadvantaged investor population rises and stock market liquidity improves. This central prediction of market microstructure theory has received wide empirical support and it has been used as a building block in numerous studies.[2] Applying this insight to our particular setting yields our second prediction: the emergence of social executives, by levelling the playing field, improves stock market liquidity and stock market participation of the previously more disadvantaged investor population, here, retail investors. We refer to this hypothesis as the *leveling the playing field hypothesis*.

We begin our empirical analysis with an assessment of our *value-relevance of executive tweets hypothesis*, which forms the basis of our *leveling the playing field hypothesis*. To gauge whether investors are able to catch a unique glimpse of how a company is performing based on what a CEO or CFO is willing to share via social media, we test whether investors can use top executives' personal tweets to help predict future earnings, above and beyond earnings forecasts by professional sell-side analysts.

Our results answer in the affirmative as we find that the tone in top executives' personal tweets is highly useful in predicting future earnings surprises. As alluded to above, top executives use Twitter to post company news, describe work-related day-to-day activities or share unrelated-to-work personal interests. In our study, we have research assistants read each tweet in our sample and categorize them into one of the above three types; we corroborate our research assistants' categorization with machine learning algorithms. When separating executive tweets into categories, we find that all of the earnings surprise predictability is coming from tweets describing work-related day-to-day activities. We find no predictability for tweets

[2] We provide more details on the theory and references to the relevant literature in Section 2.3.

describing unrelated-to-work personal interests, suggesting that, at least from an investor's perspective, the content of such tweets is not helpful.

In our second (and primary) set of tests, we assess the validity of our *leveling the playing field hypothesis*. We follow prior empirical work and capture stock market 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 activating a personal Twitter account.

Consistent with our prediction, we find that in the year after a top executive becomes social, the corresponding bid–ask spread drops substantially compared with the bid–ask spread in the year prior to the executive's becoming social; this change is above and beyond any change experienced by an observationally identical control firm over the same time frame. Also consistent with our prediction, we find that the corresponding depth and the corresponding daily turnover rise significantly. When decomposing trading into trades likely coming from retail investors and trades likely coming from institutional investors, we find that all of the observed rise in turnover is coming from retail investor trades. Relatedly, we find that when a top executive becomes social the corresponding firm's retail investor base grows substantially; by contrast, the number of institutional investors investing in the corresponding firm remains almost the same.

Executives do not become social randomly and we are mindful of the resulting self-selection bias concern. To gauge whether it is the emergence of social executives per se that generates our patterns, we examine whether our effect is stronger in situations in which investors are more likely to be informed by a top executive's social media account. In particular, we conjecture that investors are more likely to be informed by a social executive when investors pay greater attention to a social executive's Twitter account, and when a social executive is more active and sends more value-relevant tweets. Consistent with this view, we observe significantly stronger changes in liquidity and retail shareholder base when a social executive receives more re-tweets, has a wider following, posts more tweets, and posts tweets that are more informative regarding future earnings.

In a second attempt to provide evidence of causality, we use a recent Securities and Exchange Commission (SEC) ruling as a positive shock to the value-relevance of executive tweets. In the earlier half of our sample, the SEC had no clear position regarding the use of social media to broadcast company-specific news, exposing executives to concerns that when they use social media they might violate fair disclosure rules, also known as "Reg FD" (e.g., Davis Polk & Wardwell 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 after April 2, 2013, executives became more comfortable posting tweets that are pertinent to their firms' operations, which, based on our earlier evidence, are the more informative tweets to investors. If, after the SEC's clarification, executives indeed posted more work-related tweets and executive tweets as a whole became more informative to investors, our argument suggests an incremental improvement in stock market liquidity and a firm's retail investor base around the SEC's clarification.

In our first-stage analysis, we find that the fraction of work-related tweets posted by existing social media adopters indeed suddenly, substantially and permanently increases after April 2013. Correspondingly, we find that the explanatory power of executive tweets for future earnings surprises becomes much stronger after the SEC's clarification.

In our second-stage analysis, we find that the increase in the value-relevance of executive tweets around the SEC's announcement comes with incremental improvements in liquidity and retail investor base among the affected firms. As any shift in executive tweets tied to the SEC ruling is plausibly exogenous, we believe our observed improvements in liquidity and investor base point to a causal relation between social media activity by top executives and stock market liquidity and investor participation.

We see our general contribution to the literature as follows: Our study is the first to systematically document the emergence of social executives. By doing so, we are the first to show that the use of social media in financial markets has extended from investors (Chen et al. 2014; Jame et al. 2016) to the captains of some of the largest and, economically speaking, most significant corporations in the U.S. The emergence of social executives thus has significantly altered existing corporate disclosure practices.

We further show that some of the information transmitted through the personal Twitter accounts of CEOs and CFOs is value-relevant and we provide evidence that, as a result, the emergence of social executives has helped level the playing field among investors, thereby improving stock market liquidity and widening retail investor participation.

Creating a more even playing field is a key objective of regulators as a more even playing field is thought to improve the quality of financial markets and enhance economic growth (Leving and Zervos 1998; SEC 2018). Beyond its practical implications to investors, analysts, executives and investor relations departments, our findings thus also have strong normative and regulatory implications.

The rest of the paper is organized as follows. Section 2 further situates our paper in the relevant literatures and formally develops our predictions. Section 3 describes our data. Section 4 presents evidence on the value-relevance of executive tweets to investors and evidence on the economic consequences of the emergence of social executives for financial markets. Section 5 discusses alternative interpretations and Section 6 concludes.

2. Background and Hypothesis Development

In documenting the emergence of social executives and examining the value-relevance and economic consequences of executive tweets, our paper naturally relates to the large and growing literature exploring the role of social media in either affecting or predicting firm performance. Our paper also relates to the literature examining the use of social media by firm employees. In Sections 2.1-2.2, we briefly outline these two literatures and note our specific contributions to these two literatures. We then provide an overview of market microstructure theory, which, coupled with empirical findings on the usefulness and consequences of private meetings, gives rise to our empirical predictions (Section 2.3).

2.1 The Literature on Social Media and Firm Performance

Within the set of studies examining how the adoption and usage of social media *affect* firm performance, we can differentiate between those that focus on the social media activities of firms, or "firm-generated content" (FGC), and those that focus on the social media activities of consumers, or "user-generated content" (UGC). Examples of the former include Chen et al. (2015), who assess how musical artists' broadcasting activities on MySpace affect music sales; and Hong et al. (2018), who 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. Examples of the latter include Rishika et al. (2013), who show that customer activity on a firm's social networking site positively relates to the number of store visits and purchases; and Hildebrand et al. (2013), who find evidence that consumer feedback transmitted through social media negatively affects design uniqueness, customer satisfaction, usage frequency, and product valuation. Goh et al. (2013) and Chen et al. (2015) examine the relative effects of FGC and UGC on product sales and consumer purchases.

Of the studies examining how the content of social media *predicts* firm performance, some consider customer reviews (Luo et al. 2013; Huang 2018); others consider tweets across all active Twitter users (Bollen et al. 2011); Internet message boards (Antweiler and Frank 2004; Park et al. 2013); and crowdsourced equity research (Chen et al. 2014; Jame et al. 2016). The consensus across these studies is that social media content is useful in predicting future earnings and future stock returns.[3]

Compared with the above lines of work, our study is the first to note that the use of social media has extended to the CEOs and CFOs of the largest companies in the U.S. Our evidence suggests that content posted by CEOs and CFOs helps predict firm performance, thereby producing useful information to large parts of the investor population. Our evidence also suggests that the adoption of social media strongly affects the underlying firm in the form of shareholder base and stock market liquidity.

[3] In other work, Xu and Zhang (2013) find that 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

While our study is the first to assess the adoption and usage of social media by top executives, we can build on a large body of work that documents the implications of social media activity by "regular" firm employees. One stream of research in this literature investigates the blogging behavior of employees. Wattal et al. (2010) find evidence that the usage of blogs by others in an employee's network influences an employee's own blog usage, especially if those "others" are managers. Aggarwal et al. (2012) find that while employees rarely write negative posts, writing a negative post can significantly increase the readership of an employee's blog and potentially outweigh any negative effects that come from writing such a negative post. Singh et al. (2014) investigate the effects of text characteristics (including sentiment and quality) of blog posts on attracting and retaining readers; they provide evidence that the sentiment of posts affects both reader attraction and retention, but that the quality of posts affects reader retention only. Huang et al. (2015) show that the creation of leisure-related blog posts by employees has a positive spillover effect on their consumption of work-related blog posts.

A second stream of research in this literature examines the effects of social media use by employees on knowledge sharing and innovation. Gray et al. (2011) find that employees' use of social bookmarking systems is positively associated with their level of personal innovativeness as social bookmarking systems help employees access novel information. 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. Beck et al. (2014) suggest that knowledge seekers' characteristics and relational factors but not knowledge contributors' characteristics significantly drive knowledge exchange in enterprise social media. Leonardi (2014) theorizes that because enterprise social media makes communication between coworkers visible to others in the organization, employees become more aware of who knows what and who knows whom; this can lead to less duplicate work and more innovative product and service ideas. Put together, these above studies provide fairly compelling evidence that the use of social media can help employees become more productive and innovative.

Compared with regular firm employees, top executives are much more public figures. Our focus here is thus also "external," and we show how the use of social media has transformed the manner in which top executives interact with outside stakeholders of the firm.

2.3 Hypothesis Development

2.3.1 Market Microstructure Theory

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).

Market microstructure theory models the economic consequences of such informational advantages. The literature distinguishes between "informed traders" and "noise traders." While the former possess some private information, the latter have no special informational advantage. Market microstructure theory also includes "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 (Harris 2003; Madhavan 2000).

The price at which a dealer offers to buy shares from traders is the bid price; the price at which a dealer offers to sell 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 standing ready to buy or sell stocks; it represents 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 informed trader with negative private information may later 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 informed trader with positive private 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 prediction 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” and thus is reluctant to trade. 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. Market microstructure refers to the former as “depth” and to the latter as “trading volume,” or, if expressed as a fraction of shares outstanding, as “turnover.” By extension, the presence of investors with private information lowers stock market participation of the disadvantaged investor group.

To sum up, market microstructure theory predicts that a high fraction of investors with private information dries up stock market liquidity in the form of high spreads, low depth and low turnover; it also lowers participation by the investors without such private information. As more private information becomes public and as the playing field becomes more level, stock market liquidity improves, and investor participation widens.

This central prediction of market microstructure theory has received wide empirical support across a number of settings. Stoll (2000) and Holden et al. (2014), among others, argue that there are more investors with private information among stocks with low market capitalization, low price per share and high volatility. In line with such argument and market microstructure theory, Stoll (2000) and Holden et al. (2014) find that such stocks have significantly wider spreads. In a cross-country study, Eleswarapu and Venkataraman (2006) argue that higher quality accounting standards help improve the flow of public information and lower the fraction of investors with private information. In line with their conjecture and consistent with market microstructure theory, they provide evidence that liquidity increases with the quality of accounting standards. Similarly, a large body of literature in accounting provides evidence that improved corporate disclosure lowers information heterogeneity among investors, thereby improving stock market liquidity (e.g., Coller and Yohn 1997; Leuz and Verrecchia 2000; Lang et al. 2012).

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

In this paper, we argue that the emergence of social executives has (further) helped level the playing field among investors. We begin by explaining an important source of information heterogeneity among investors. We then argue how the presence of social executives helps mitigate information heterogeneity coming from that particular source.

i) An Important Source of Information Heterogeneity among Investors: 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. In the U.S., 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 (2018) 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 yield the occasional "hard" piece of information (SEC 2002, 2003, 2004, 2010).[4] Responses to the broad questions and an executive's general body language and tone also provide a significant amount of "soft" information to

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

investors (SEC 2004; Wall Street Journal 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).

Private meetings are generally arranged by investment banks, and the investors in attendance 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 (Wall Street Journal 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 among 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.[5] Since the enactment of Reg FD, the SEC has conducted only five Reg FD enforcement actions against private meetings (Park 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

[5] 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 is negligible. Even when such an enforcement action occurs, the associated penalty is trivial.

ii) *Value-Relevance of Executive Tweets Hypothesis*

Starting in 2008, CEOs and CFOs in the largest publicly traded U.S. 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 3, we focus our analysis on Twitter.

As alluded to in the introduction, 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.

CEOs and CFOs probably possess the most comprehensive information about how a company is performing. They are also the key decision makers in a company. Yet, outside of those privy to private meetings with CEOs and CFOs, hearing from a top executive constitutes a rare event. Using a custom dataset, Kim and Meschke (2014) find that even within the subsample of CEOs who appear on CNBC at least once, the average CEO appears only 0.82 times a year.

Prior to the emergence of social media, even hearing directly from a firm was an uncommon event. The SEC requires that all publicly traded firms inform investors of any material event via Form 8-K. But Noh et al. (2018) find that the average firm files only eight 8-Ks a year, four of which are the quarterly and annual earnings announcements. Firms also issue press releases to inform investors of any events that they deem not material enough to warrant Form 8-K, but that firms still consider potentially useful to investors. Yet, Soltes (2010) finds that the average firm issues only 24 such press releases a year.

By comparison and as discussed further in Section 3.1, towards the end of our sample period, the average top executive in our sample posts 118 tweets a year, 60 of which are work-related tweets. We speculate that investors are able to receive unique clues regarding how a company is performing based on such active use of Twitter. Clues may arrive in the form of tweets announcing company news or tweets describing work-related day-to-day activities. Section 3.1 and Figure 1 provides examples of such clues. To a smaller degree, even tweets describing personal interests may provide value-relevant information to investors, as any positive or negative development at work could carry over to a top executive's personal life. Our first hypothesis, which we label *value-relevance of executive tweets hypothesis,* thus is:

Hypothesis 1: *Social executives' tweets provide unique and value-relevant information to investors. Work-related tweets are more informative to investors than tweets describing unrelated-to-work personal interests.*

iii) Leveling the Playing Field Hypothesis

Clearly, the presence of social executives is no substitute to private meetings with top executives as a means of staying informed. Still, to the degree that our *value-relevance of executive tweets hypothesis* holds true, since any investor can access any top executive's public Twitter account, the emergence of social executives nevertheless marks a democratization of investor access to top executives for unique and value-relevant information to which prior to the emergence of social executives most investors had no access. We therefore hypothesize that the emergence of social executives has helped create a more level playing field among investors, in particular if investors widely and closely follow a social executive and if a social executive is particularly active on social media and posts particularly value-relevant tweets.

Based on market microstructure theory, 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 the previously disadvantaged investor group. Applying market microstructure theory to our particular setting yields our second (and primary) hypothesis, which we label *leveling the playing field hypothesis*:

Hypothesis 2: *The emergence of social executives, by leveling the playing field, improves stock market liquidity and widens a firm's retail investor base (but does not widen a firm's institutional investor base).*

Hypothesis 2a: *The effects on stock market liquidity and retail investor base are positively moderated by how widely and closely followed a social executive is, …*

Hypothesis 2b: *… and by how active a top executive is on Twitter and how informative the average top executive tweet is to investors.*

We now describe the data we use to test our two hypotheses.

3. DATA

3.1 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, as 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 U.S. As of December 2014, the end of our sample period, Twitter had 284 million active users posting approximately 500 million tweets a day.[6]

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.[7] Through this labor-intensive process, we determine that

[6] https://about.twitter.com/company.

[7] 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.

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 available on our website.[8]

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. These tweets include "original" tweets posted by a top executive as well as tweets in which a top executive re-tweets, replies to, or comments on another user's original tweet. The information that we collect about each tweet includes account identifier, tweet identifier, date, time, content of the tweet, and a tweet's number of re-tweets.

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 substantially over time. Our full sample comprises 155 tweeting executives posting a total of 47,119 tweets.[9]

In Panel B of Table 1 we separate the number of executives and their tweets by four-digit-GICS industry groups. There are 24 GICS industry groups. We find that there are social executives in all but one GICS industry group. 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. Panels C and D show that 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.

[8] 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 for personal Facebook accounts. When we sent "friend" requests to the 72 CEOs and CFOs whom we identify as having personal Facebook accounts, only five (6.9%) accepted our friend request.

[9] The number of active executives in any given year does not reach the 155 figure because some executives post tweets only sporadically.

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 or current set of interests. 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. 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 gauge the distribution of executive tweets along these three types, we recruit eight research assistants (RAs) and ask them to classify each tweet in our sample into one of the three types: Type 1 (company-related news announcement), Type 2 (work-related day-to-day activities), Type 3 (unrelated-to-work personal interests). We first define each of the three types to the RAs as in the sentence above. We then provide sample tweets for each type (as in Figure 1). We give our RAs a sufficient amount of time (three months) to complete the classification task. Each tweet is first read by three RAs. We categorize a tweet into the type into which at least two RAs (i.e., the majority) 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 4.7%, 49.2%, and 46.1% for Type 1, Type 2, and Type 3 tweets, respectively.

To gauge the validity of our RAs' tweet categorization, we implement supervised machine learning algorithms to re-classify each tweet in our sample into one of our three types. We first randomly select a small sample of 5,000 tweets and we use the tweet classifications of our RAs to train our algorithms. We run the following well-known machine learning algorithms with Scikit-Learn in Python: Convolutional Neural Network, Logistic Regression, Naïve Bayes, Random Forest, and Support Vector Machine. We also run the ensemble method by combining all the five classifiers into one meta-classifier.

After training our various algorithms on our initial random sample of 5,000 tweets, we then apply the models to classify the remaining 42,119 tweets. Online Appendix Table 1 shows for what fraction of tweets our RAs' categorization of tweets and our machine-learning based categorizations agree. In short, depending on which particular machine learning algorithm we use, we find that for between 66.4% and 73.3% of tweets, "humans" and "machines" arrive at the same classification (e.g., both agree that a given tweet is of "Type 1"). Online Appendix Table 2 shows the distribution of tweets across the three types for each machine learning algorithm. The results are similar across the various algorithms. The ensemble method, for instance, determines that 1.0%, 47.9%, and 51.1% of tweets are Type 1, Type 2, and Type 3 tweets, respectively. These numbers are similar to those under our RA-based categorizations. We later present results for both our RAs' categorization and all of our machine-learning based categorizations.

3.2 Outcome Variables and Key Control Variables

Having described the source of our key explanatory variable, we now turn to the construction of our dependent variables. We also highlight key control variables. We report the summary statistics of these variables in Table 2.

3.2.1 Stock Market Liquidity and Investor Base

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 U.S. 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 seven-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 et al. 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 for trade at the best ask quote plus the dollar amount available for 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 improve model fit.

Retail Turnover (*Institutional Turnover*) is the number of shares traded by retail investors (institutional investors) on a given day, divided by the number of shares outstanding.[10] In essence, our turnover variables compute the fraction of total shares outstanding that are traded on a given day. In our tables and analyses, we express our turnover variables 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

[10] Most equity trades by retail investors take place off-exchange (Battalio et al. 2016). In TAQ, the off-exchange has the exchange code "D." Trades executed on exchange code "D" can thus be categorized as retail trades. Moreover, Boehmer et al. (2017) note that retail traders typically receive a small fraction of a cent price improvement over the National Best Bid or Offer for market orders (ranging from 0.01 to 0.2 cents), while institutional orders tend to be executed at whole or half-cent increments. Boehmer et al. thus argue that one can further categorize trades as retail purchases (sales) if the trade took place at a price just below (above) a round penny.

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.

3.2.2 Firm-Managed Twitter Accounts and Facebook Pages

To account for firms' social media activities, we collect data on firm-managed accounts from both Twitter and Facebook. Jung et al. (2018) report that, as of 2015, almost half of all S&P 1500 firms have firm-managed Twitter accounts. Most tweets coming out of firm-managed Twitter accounts contain hyperlinks to public press releases (e.g., "Link to $AA 1Q 2012 press release: http://t.co/CdMy5u3O"). The information broadcast through firm-managed Twitter accounts is thus fundamentally different from the information transmitted through top executives' personal Twitter accounts. Blankespoor et al. (2014) and Jung et al. (2018) 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.

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, a top executive 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. We construct variables based on both the number of tweets coming out of firm-managed Twitter accounts and the tone of such tweets (please see Figure 2 for more details).

Facebook is another popular social media channel used by firms to promote their products and services and engage with their customers. We find that 134 out of 155 social executives work for firms that have a firm-managed Facebook page. Unlike most personal Facebook profiles that restrict access to friends only, all firm-managed Facebook pages in our sample are public accounts and can be viewed by anyone with a Facebook account. Here too, we construct variables based on both the number of Facebook posts and the tone of such posts.

3.2.3 Other Variables

To assess whether information transmitted through tweets is distinct from news announcements, we control for news transmitted through the Dow Jones Newswires (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*.[11] We manually download DJNS articles for the stocks in our sample via the Factiva database. We then construct variables based on both the tone and the number of DJNS articles.

SA is a leading social-media platform that provides crowd-sourced equity research articles in the U.S. 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. Here too, we construct variables based on both the tone and the number of SA articles and SA commentaries. Prior literature provides evidence that both DJNS articles and SA articles/commentaries have high informational value and therefore should serve as meaningful controls for company news or changes in company perception (Tetlock 2007; Tetlock et al. 2008; Chen et al. 2014).

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

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

interviews (Green et al. 2017),[12] and we compute various executive characteristics using data from the Execucomp database (also described in Figure 2).[13]

4. ANALYSES AND RESULTS

4.1 Value-Relevance of Social Executives' Tweets

Our first hypothesis is that social executives' tweets provide unique and value-relevant information to investors. We should thus be able to use executive communication to predict a firm's operating performance above and beyond what other market participants predict. We also posit that work-related tweets are more informative to investors than tweets describing unrelated-to-work personal interests.

To assess the validity of these conjectures, we build on a large literature, which shows that the information contained in a text can be quantified by how frequently terms from a given word list appear in such a text (please see Loughran and McDonald (2016) for a survey of this literature). The most commonly employed word list in accounting and finance research is the negative words list of Loughran and McDonald (2011), which was developed specifically for analysis of financial information.[14] We compute how frequently these negative words appear in social executives' tweets and we assess whether the fraction of negative words helps predict a firm's operating performance above and beyond what professional sell-side analysts predict.

Our specific regression equation draws from Tetlock et al. (2008) and Chen et al. (2014), who examine how the fraction of negative words in print articles and social media content relate to future earnings above and beyond what sell-side analysts predict:

[12] 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.

[13] 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.

[14] The negative word list can be found at: https://drive.google.com/file/d/0B4niqV00F3msQ0kySzQ1c0ZyRW8/view

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

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. Our key independent variable, *%Neg Executive Tweets*, 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.[15] If top executive tweets impart unique and value-relevant insights, *%Neg Executive Tweets* should contain information regarding future earnings above and beyond what professional sell-side analysts predict. We thus expect a negative coefficient estimate for *%Neg Executive Tweets*.[16]

α_t represent year-month fixed effects. X includes the following control variables: *Log(1 + #Executive Tweets)*, *Log(1 + #Company Tweets)*, *%Neg Company Tweet*, *Log(1 + #Company FB Posts)*, *%Neg Company FB Posts*, *Log(1 + #DJNS Articles)*, *%Neg DJNS Articles*, *Log(1 + #Seeking Alpha Articles)*, *%Neg Seeking Alpha Articles*, *Log(1 + #Seeking Alpha Comments)*, *%Neg Seeking Alpha Comments*, *Forecast Dispersion*, *Forecast Revisions*, *Log(Size)*, *Book-to-market*, *Share Turnover*, *Abnormal Returns*$_{-2}$, *Abnormal Returns*$_{-30,-3}$, and *Abnormal Returns*$_{-252,-31}$. All variables are defined in Figure 2. We cluster our standard errors by firm and year-month.

We report our findings in Table 3. Consistent with *Hypothesis 1*, the regression results shown in Column 1 indicate that views expressed through tweets help predict future earnings surprises. The coefficient estimate for *%Neg Executive Tweets* equals -0.105 (*t*-statistic=-2.83), suggesting that a one-

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

[16] We are primarily interested in whether social executives' tweets can help predict future earnings surprise, thereby providing useful and unique information to investors. In additional tests reported in Online Appendix Figure 1, we explore whether social executives post tweets in anticipation of a forthcoming earnings announcement. In particular, we look at social executives' tweeting activity around each earnings announcement and plot the average number of tweets per week and the corresponding average fraction of negative words in the five weeks both before and after an earnings announcement. In short, we do not observe an increase in the number of or a change in the tone of tweets prior to earnings announcements; we also do not observe a more positive tone in tweets prior to a positive earnings surprise or a more negative tone in tweets prior to a negative earnings surprise.

standard-deviation increase in the fraction of negative words lowers future earnings surprises by 0.14%. To put this number in perspective, the mean and median of earnings surprise in our sample are 0.03% and 0.06%, respectively.

Column 2 of Table 3 shows that the explanatory power of %*Neg Executive Tweets* increases substantially after April 2 2013; on April 2 2013, the SEC embraced social media as a channel through which firms and executives may disseminate non-material information about the firm. To preview, in Section 4.3.2, we utilize the SEC's embrace of social media to provide additional evidence on the effect of social media activity by top executives on stock market liquidity and investor base.

In Column 3 of Table 3 we show results when breaking up the %*Neg Executive 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. Consistent with *Hypothesis 1* we find that the earnings-surprise predictability is much stronger for Type 2 tweets than for Type 3 tweets. In particular, we find that all of our earnings-surprise predictability comes from Type 2 tweets, which are tweets describing an executive's work-related day-to-day activities; the estimate for the fraction of negative works in Type 2 tweets is -0.230 (*t*-statistic = -2.92). Type 3 tweets, which are tweets related to an executive's personal interests, and Type 1 tweets, which are company-news announcements, display no predictability; the estimates are 0.036 (*t*-statistic = 0.24) and -0.040 (*t*-statistic = -0.20), respectively. In untabulated analysis, we find that when we remove our news-related control variables based on Dow Jones Newswires and Seeking Alpha, the coefficient estimate for the fraction of negative words in Type 1 tweets becomes economically meaningful and statistically marginally significant (-0.224, *t*-statistic = -1.88). That is, it appears that Type 1 tweets are somewhat value-relevant. At the same time, it seems that news shared in Type 1 tweets is simultaneously broadcast through other channels such as public press releases or regulatory, which, in turn, are captured by our control variables. Unlike the information revealed in Type 2 tweets, the information contained in Type 1 tweets is thus not unique.[17]

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[17] Our results based on tweet types are robust to both our manual classification of tweet types and the classifications of all our six machine learning algorithms mentioned in Section 3.1 (Online Appendix Table 3).

The coefficient estimates of the control variables in Table 3 are mostly in line with expectations. To give some examples, we find that sentiment in DJNS articles is a very strong predictor of future earnings surprises, which is consistent with Tetlock et al. (2008). As Tetlock et al., we also observe strong positive coefficient estimates for *Forecast Revision* and our measures of past one-year- and past one-month-stock market performance; and as Tetlock et al., we observe negative estimates for *Forecast Dispersion*, *Size*, and *Share Turnover* although some of our negative estimates are not statistically significant, which, given our comparatively small sample size, we do not find surprising.

In our particular setting, we find that sentiment in Facebook posts, sentiment in Seeking Alpha content and sentiment in tweets coming out of firm-managed Twitter accounts are not reliable predictors of future earnings surprises. The lack of significance for Seeking Alpha content is somewhat at odds with Chen et al. (2014), albeit the estimate for Seeking Alpha articles does have the expected sign. Here, too, we believe that our comparatively small sample size is the key.[18]

Put together, the results reported in this subsection show that personal tweets describing work-related day-to-day activities help predict future operating performance above and beyond what professional sell-side analysts predict. This finding is consistent with our *value-relevance of executive tweets hypothesis* that executive tweets provide unique and value-relevant information to investors.

4.2 Economic Consequences of the Emergence of Social Executives

We now turn to the impact of the emergence of social executives on stock market liquidity and a firm's investor base (*Hypothesis 2*). For stock market liquidity, our inferences 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 directly to top executives' becoming social, we conduct a difference-in-

[18] When not restricting our sample to firms with social executives, we find that Seeking Alpha sentiment does reliably predict future earnings surprises. Also, to the best of our knowledge, we are the first to examine whether sentiment in Facebook posts and tweets coming out of firm-managed Twitter accounts is a reliable predictor of future earnings surprises. In that regard, our lack of reliable findings is neither consistent nor inconsistent with prior literature.

differences analysis within a regression framework.[19] 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 its liquidity over the one-year period following the top executive's becoming social.[20] We repeat this procedure for treated firm *i*'s control firm and study changes in treated firm *i*'s liquidity above and beyond any change experienced by its control firm.

We find control firms through propensity-score matching based on a host of executive and firm characteristics (Caliendo and Kopeining 2008; Dehejia and Wahba, 2002; Rosenbaum and Rubin 1983).[21] Our matching results reported in Online Appendix Table 5 suggest that all variables between the treated group and the matched control group are balanced with standardized differences of less than 5%.

While non-material for our main results,[22] to minimize the effect of potentially confounding factors, in our event window, we remove the trading days immediately surrounding a top executive adopting Twitter. To be conservative and further minimize the effect of confounding factors, we do not include Twitter adoptions for which 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. As mentioned in Section 3.2.3, 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 therefore be captured by our DJNS and SA variables. Our

[19] 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. In our first test, we plot the median of our dependent variables for both the control and treatment groups over time in Online Appendix Figure 2. We find that the two curves for each of the dependent variables 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 in Online Appendix Table 4. Here too, our results suggest that the parallel-trend assumption holds.

[20] 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.

[21] The executive and firm characteristics 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*, and *Log(Firm Age)*.

[22] The results without imposing any of the restrictions described in this paragraph are similar to the results presented in the paper and they are available upon request.

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 141 Twitter adoptions (282 firms in total; 141 treated firms and 141 control firms) and 91,805 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 four liquidity measures, *Spread*, *Log(Depth)*, *Retail Turnover*, or *Institutional Turnover*. α_i and δ_t are firm and year-month-day fixed effects. Firm fixed effects control for any unobservable time-invariant firm characteristics. Year-month-day 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* employs or will employ a social executive 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* thus 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 year-month-day fixed effects.

X contains the following control variables. We use the following variables to control for firm-initiated disclosures: *Log(1 + #Executive Tweets)*, *Log(1 + #Company Tweets)*, *%Neg Company Tweet*, *Log(1 + #Company FB Posts)*, and *%Neg Company FB Posts*. We use the following variables to control for firm-specific news transmitted through information intermediaries*: Log(1 + #DJNS Articles)*, *%Neg DJNS Articles*, *Log(1 + # Seeking Alpha Articles)*, *%Neg Seeking Alpha Articles*, *Log(1 + #Seeking Alpha Comments)*, *%Neg Seeking Alpha Comments*, *Earnings Announcement*, *Log(1 + #Analysts)*, and *Institutional Holding*. Following Blankespoor et al. (2014), we also include *Abs. Abn. Ret* and *Share 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 *Retail Turnover* or *Institutional 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 et al. 2014).[23] We thus also control for *Size*, *Book-to-Market*, *Log(Asset)*, *Log(Price)*, *Monthly Volatility*, and *Log(#Shareholders)*. Finally, to control for potential selection bias, we use the Heckman correction procedure (Heckman 1979) and we include the Inverse Mills Ratio (*IMR*) as of the previous year.[24] Specifically, we regress the Twitter adoption status in a year from 2008 through 2014 on a set of lagged independent variables predicting Twitter adoption (the results of which we present in Online Appendix Table 7). For each executive/year, the *IMR* is the ratio of the probability density function to the cumulative distribution function and it represents the likelihood that an executive adopts Twitter in a given year. We cluster our standard errors by both firm and time.

We report our findings in Table 4. Column 1 of Table 4 shows that when the dependent variable is *Spread*, our model produces a significant negative coefficient estimate for *TreatmentGroup×AfterBecomingSocial*, -0.027 (*t*-statistic = -4.31), suggesting that when a top executive becomes social, the corresponding firm's *Spread* disproportionately decreases by 0.027%. 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 *Spread* by 24.3 percentage points (= -0.027%/0.111%). The implied decrease of 24.3 percentage points is substantial. We do not deem it implausible however: *Spread* is defined as the dollar bid-ask spread scaled by the stock price. Given the average stock price of $32 across our sample firms, our average *Spread* of 0.111% implies an average dollar bid-ask spread of $0.036. Therefore, even if the dollar bid-ask spread decreased by one penny, which is the

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[23] 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 are differenced-out.

[24] Other work that uses the Heckman correction procedure within a difference-in-differences framework includes (Neuhauser and Raphael 2004; Chen et al. 2016) among others. Analyses without the Heckman correction procedure produce results very similar to the ones presented in this study (Online Appendix Table 6).

minimum by which a dollar bid-ask spread can change, the new dollar bid-ask spread would be $0.026 and the new *Spread* would be 0.081%, translating into a 28 percentage points decrease in *Spread* (from 0.111% to 0.081%). In that regard, our observed 24.3 percentage points decrease is certainly large and economically substantial. It does not seem implausible though.

As shown in Columns 2 through 4, regarding *Log(Depth)*, the coefficient estimate for *TreatmentGroup×AfterBecomingSocial* equals 0.023 (*t*-statistic = 4.78), suggesting that when a top executive becomes social, the corresponding firm's depth increases by 2.3 percentage points. Regarding *Retail Turnover* and *Institutional Turnover*, the coefficient estimate for *TreatmentGroup×AfterBecomingSocial* equals 0.010 (*t*-statistic = 3.69) and 0.004 (*t*-statistic = 0.50), respectively. The former estimate implies that daily retail turnover of firms whose top executives start tweeting increases by one basis point. Given that the average daily retail turnover in the month prior to a top executive's becoming social is 8.2 basis points, our result suggests that a top executive's becoming social increases daily retail turnover by 12.2 percentage points (= + 1 basis point/8.2 basis points). Since institutional turnover experiences almost no change, the fraction of trades that are retail trades (as opposed to institutional trades) increases substantially after an executive becomes social. All these findings are consistent with our *leveling the playing field hypothesis*.

In Columns 5 and 6, we report results obtained when re-estimating regression equation (3) but replacing the liquidity-based dependent variables with *Log(#Retail Investors)* and *Log(#Inst. Investors)*. Since these variables can be captured only at an 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)*. Our previous year-month-day fixed effects are now year fixed effects. 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 1,306 firm/year observations.

As presented in Columns 5 and 6, we find that, when a top executive becomes social, the corresponding firm experiences a 10.5 percentage points growth in its retail investor base (t-statistic = 2.77); for reference, the average number of retail shareholders in our sample is 47,550. We observe no association between top executives' becoming social and the number of institutional investors; the coefficient estimate for *TreatmentGroup×AfterBecomingSocial* is 0.028 (t-statistic = 1.21). The fact that we observe a rise in the number of retail investors, but not in the number of institutional investors, coupled with our earlier result that we observe a spike in trades coming from retail investors, but not from institutional investors, is strongly in line with our argument that the emergence of social executives has helped level the playing field and increased stock market participation of retail investors relative to institutional investors.

As before, the coefficient estimates of the control variables are generally in line with expectations and consistent with the findings in Blankespoor et al. (2014). For instance, we find a significant negative coefficient estimate for *Log(1 + #Analysts)* and a significant positive coefficient estimate for *Abs. Abn. Ret* in our *Spread* analysis; we find significant positive estimates for *Log(1 + #Analysts)*, *Institutional Holding*, and *Share Turnover* in our *Log(Depth)* analysis; in particular, we also find a strong positive estimate for *Log(1 + # CompanyTweets)* in our *Log(Depth)* analysis, consistent with Blankespoor et al.'s argument that the dissemination of firm-initiated news via social media helps reduce information asymmetry.[25]

4.3 Moderating Effects and Natural Experiment

Our evidence to this point, while highly suggestive of our *leveling the playing field hypothesis*, is not free of alternative interpretations. For instance, despite our use of propensity-score matching and Heckman correction procedure within a difference-in-differences framework, one could argue that a top executive's

[25] As alluded to in our data section, the tweets in our study include original tweets posted by a top executive ("unidirectional tweets") as well as tweets in which a top executive re-tweets, replies to, or comments on another user's original tweets ("conversational tweets"). In separate tests, we assess whether social executives who post relatively more conversational tweets have a differential impact. We have no prior on what to expect, but we believe any result should be descriptively interesting. For each social executive, we compute the fraction of tweets that are conversational. We then split our sample in half based on the fraction of tweets that are conversational. As presented in Online Appendix Table 8, we find that while liquidity and retail investor base improve in both subsamples, the improvements are somewhat stronger in the subsample of social executives with relatively more conversational tweets.

decision to become social may reflect a change in a firm's overall strategy or a shift in branding efforts, which, in turn, could impact stock market liquidity and shareholder base.

4.3.1 The Roles of Twitter Usage and Twitter Content

Our first attempt to establish that it is truly our *leveling the playing field hypothesis* that generates at least parts of our findings builds on the following premise: if our conjecture is accurate, then our findings should be stronger in situations in which investors are more likely to be informed by the presence of a social executive. On the "consumption" side, this implies that our liquidity and retail shareholder base effect should be stronger when investors rely to a greater degree on a social executive's tweets. This is our *Hypothesis 2a*, which posits that the *effects on stock market liquidity and retail investor base are positively moderated by how widely and closely followed a social executive is.*

On the "production" side, this implies that our liquidity and retail shareholder base effect should be stronger when a social executive posts more and more value-relevant tweets. This is our *Hypothesis 2b*, which posits that the *effects on stock market liquidity and retail investor base are positively moderated by how active a top executive is on Twitter and how informative the average top executive tweet is to investors.*

To test *Hypothesis 2a*, we split our sample in half based on a social executive's total number of re-tweets in the first year of a top executive becoming social. We then estimate regression equation (3) separately in each of the two subsamples and assess whether the estimate for *TreatmentGroup* × *AfterBecomingSocial* is different across the above- and below-median subsamples. We repeat this procedure based on a social executive's total number of followers.[26] For reference, when splitting our sample based on the number of re-tweets, we find that the average tweet in the above-median subsample receives 71,696 re-tweets; in the below-median subsample, the average tweet receives only 13 re-tweets. When slicing our sample based on the number of followers, we find that the average social executive in the

[26] Unlike for re-tweets, we do not have historical data on the number of followers. We only have the number of followers as of the time we scraped the data, which, also, marks the end of our sample period. The total number of followers is thus as of the end of our sample period.

above-median subsample has 135,402 followers; the average social executive in the below-median subsample has only 128 followers.

To test *Hypothesis 2b*, we split our sample in half based on a social executive's total number of tweets posted in the first year of a top executive becoming social. We repeat this procedure for the fraction of tweets that are work-related. We then estimate regression equation (3) separately in the above- and below-median subsamples. The average social executive in the above-median subsample posts 189 tweets in the first year of becoming social; the average social executive in the below-median subsample posts only four tweets. When separating social executives by the fraction of tweets that are work-related, we find that for social executives in the top half, 80.48% of tweets are work-related; for social executives in the bottom half, only 13.38% of tweets are work-related.

Table 5 shows that in almost all regression specifications the improvements in stock market liquidity and retail investor base are coming entirely from firms in which a top executive's tweets are re-tweeted more often, a top executive's Twitter account has more followers, and a top executive posts more tweets and more work-related tweets. For firms that are in the bottom half with respect to the above Twitter usage and Twitter content characteristics, we observe little to no improvements in liquidity and retail investor base around the emergence of a social executive.

To provide an example, in the subset of firms with social executives receiving an above-median number of re-tweets (and their corresponding control firms), the estimates for *TreatmentGroup* × *AfterBecomingSocial* for *Spread*, *Log(Depth)*, *Retail Turnover*, and *Log(#Retail Investors)* are -0.064 (*t*-statistic = -8.65), 0.052 (*t*-statistic = 6.17), 0.018 (*t*-statistic = 4.37), and 0.451 (*t*-statistic = 2.73), respectively. All of these estimates are highly significant, both statistically and economically. In comparison, the corresponding estimates in the below-median subset are significantly weaker. The estimates are -0.013 (*t*-statistic = -1.02), 0.011 (*t*-statistic = 2.01), -0.002 (*t*-statistic = -0.65), and -0.071 (*t*-statistic = -0.46), respectively. The non-result in the below-median subset appears sensible to us as we do not believe investors are likely informed by the presence of a social executive whose average tweet receives only 13 re-tweets, who has only 128 followers, who posts only four tweets in her first year and who posts few work-related tweets (13.38%).

In additional analyses we repeat the above analysis, but we now split the sample into terciles (as opposed to split the sample in half). As shown in Online Appendix Table 9, we find that in all cases but one, stock market liquidity around the emergence of a social executive improves *monotonically* from the bottom through the top tercile.[27] For instance, when the dependent variable is *Spread* and when sorting based on the number of re-tweets, we find that the estimate for *TreatmentGroup* × *AfterBecomingSocial* rises from -0.002 (*t*-statistic = -0.34) in the bottom tercile to -0.027 (*t*-statistic = -1.86) in the middle tercile to -0.164 (*t*-statistic = -9.35) in the top tercile. When the dependent variable is *Log(Depth)* and when sorting based on the number of tweets, the estimate for *TreatmentGroup* × *AfterBecomingSocial* rises from 0.014 (*t*-statistic = 1.64) in the bottom tercile to 0.026 (*t*-statistic = 3.27) in the middle tercile to 0.039 (*t*-statistic = 4.53) in the top tercile. The only instance liquidity does not improve monotonically occurs when the dependent variable is *Log(Depth)* and when we sort firms based on the number of followers, in which case the estimate for *TreatmentGroup* × *AfterBecomingSocial* changes from 0.006 (*t*-statistic = 0.74) in the bottom tercile to 0.061 (*t*-statistic = 7.48) in the middle tercile to 0.048 (*t*-statistic = 5.24) in the top tercile. Still, we believe the near monotonicity helps build confidence in the validity of our exercise.

4.3.2 The SEC's "Blessing of Social Media" in 2013

Our second attempt to establish that it is truly our *leveling the playing field hypothesis* that generates at least parts of our findings is a difference-in-differences analysis around the SEC's embrace of social media on April 2, 2013. Until April 2, 2013 it was unclear whether executives posting company-related information on social media accounts were acting in line with Reg FD.[28] On July 5, 2012 Reed Hastings,

[27] Since we observe investor base only at an annual frequency and thus only have a limited number of observations in our investor base regression analysis, we cannot split our investor base sample into terciles and estimate separate regression equations within each tercile.

[28] As alluded to in the introduction, prior to April 2, 2013, the SEC had no clear position regarding the use of social media to broadcast company-specific news, exposing executives to concerns that when they use social media they might violate fair disclosure rules, also known as "Reg FD" (e.g., Davis Polk & Wardwell 2013).

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 feel 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 conjecture, 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, "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 conjecture, 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% from March 2013 to May 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. The observed 9.49% shift over the course of two months thus represents a dramatic shift. As shown in Figure 3, the discontinuous jump in the fraction of work-related tweets does not revert.

Our previously reported findings in Section 4.1 suggest that work-related tweets are more useful to investors than tweets that are not work-related. If so, the above noted shift made executive tweets as a whole more informative, and Column 2 of Table 3 reports that the explanatory power of executive tweets for future earnings surprises indeed increases substantially after April 2, 2013. If there is a causal link between top executives' social media activity and our outcome variables via levelling the playing field, firms whose top executives had adopted Twitter prior to the SEC's clarification should thus experience incremental improvements in stock market liquidity and retail investor base around the SEC's announcement.[29]

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 (i.e., treated firms) and their matched firms; matched firms are constructed as in Section 4.2:

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

Our main variable of interest is *TreatmentGroup* × *Post SEC Embrace*. *TreatmentGroup* equals one if the observation belongs to a firm with a social executive and zero otherwise. For each treated firm and its corresponding matched control firm, *Post SEC Embrace* equals one if the observation falls after April 2, 2013 and zero otherwise. Both *TreatmentGroup* and *Post SEC Embrace* are absorbed into the fixed effects.

For the spread, depth, and turnover analyses, which are conducted at a 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 an 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).

[29] Since our test is conducted within the sample of firms whose top executives had already adopted Twitter prior to the SEC's clarification, our test also helps mitigate the reverse causality concern that some executives decide to adopt Twitter in anticipation of a growth in retail investor base.

Table 6 shows that the coefficient estimates for *TreatmentGroup* × *Post SEC Embrace* are -0.062 (*t*-statistic of -7.10) for the spread analysis, 0.138 (*t*-statistic = 11.13) for the depth analysis, and 0.026 (*t*-statistic = 1.97) for the retail turnover analysis; institutional turnover continues to yield insignificant results. That is, in conjunction with the striking and permanent shift in social executives' tweets towards tweets pertinent to their firms' operations, which made executive tweets as a whole more useful to investors, firms with social executives experience an incremental drop in their spreads, an incremental rise in their depths, and an incremental rise in their retail trading volumes after the SEC's clarification. The results presented in Column (5) of Table 6 indicate that firms with social executives also experience an incremental rise in the number of retail investors. The estimate is 0.117 (*t*-statistic = 2.34). We continue to see no change in the number of institutional investors.[30]

In summary, our subsample analysis on existing Twitter adopters around a plausibly exogenous shock to Twitter usage indicates a causal relationship between top executives' social media activity and improved market liquidity and wider investor bases via leveling the playing field.

5. DISCUSSION AND ALTERNATIVE INTERPRETATIONS

While we believe that our analyses and results are perhaps most naturally motivated and interpreted by the idea that social executives provide value-relevant information to which prior to the emergence of social executives most investors had no access to, there are alternative interpretations of our results, some of which are hard to rule out completely.

For example, as alluded to earlier, a top executive's decision to become social may coincide with a change in a firm's overall strategy or a shift in branding efforts. Relatedly, a change in a top executive's social media activity may be part of a larger change in a firm's social media campaign.

[30] In results tabulated in Online Appendix Table 10, we separately consider the subset of social executives who activate their Twitter accounts before (after) April 2013 (i.e., the SEC embrace) and their corresponding control firms and we repeat our analysis in Table 4 in both subsets to examine whether the estimate for *TreatmentGroup x AfterBecomingSocial* is different across the two subsets. We find that when a social executive emerges post April 2013, the liquidity and retail shareholder effects are stronger than when a social executive emerges pre April 2013.

We find our evidence from the analysis around the SEC's embrace of social media helpful in (partially) discriminating against these two possibilities. In particular, regarding the former that a change in a top executive's social media activity may coincide with a change in a firm's overall strategy or a shift in branding efforts, it seems unlikely that firms with social executives would all happen to jointly implement a change in strategy or a branding shift around the time the SEC embraced social media.

Regarding the latter that a change in a top executive's social media activity may be part of a larger change in a firm's social media campaign, we note that in our regression analysis we include control variables capturing two of a firm's most popular social media channels, Twitter and Facebook. In additional tests, we specifically assess whether the SEC's embrace of social media came with an increase in firms' social media activities after April 2013, which might explain the observed incremental improvement in stock market liquidity and retail investor participation for the sample of 84 treated firms that had social executives prior to the SEC embrace. In particular, we plot the average number of firm tweets and the average number of firm-managed Facebook posts for each year-month from 2011 through 2014 for both the treatment and the control groups. As shown in Online Appendix Figure 3, there is no meaningful differential change in Twitter and Facebook activity across treatment and control firms after the SEC's embrace. That is, the striking and permanent shift in Twitter content among social executives around the SEC's embrace is *not* accompanied by any noticeable changes in firms' Twitter and Facebook activities. These findings suggest that top executives' change in social media activity is *not* part of a larger change in firms' social media campaign.

Another alternative story, which we call the *grabbing investor attention story* is that social executives, through their tweets, draw the attention of "bounded-rational investors" who otherwise would not have paid attention to the relevant firm and, as a result, would not have considered the relevant firm for investment.[31] This, in turn, translates to greater trading activity in the relevant stock and a wider shareholder

[31] 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). Likely as a result, prior work finds evidence that bounded-rational investors consider only stocks that exhibit salient attributes that grab their attention (e.g., Hirshleifer 2001, Grullon et al. 2004, Barber and Odean 2008).

base. Another somewhat related possibility is that top executives communicating through social media are people who, in general, have great charisma and allure, and their allure only becomes magnified through their social media usage. We refer to this possibility as the *charisma story*.

We cannot reject the possibility that either the *grabbing investor attention story* or the *charisma story* are responsible for parts of our findings. We are not sure this is hugely critical for our analysis as our *leveling the playing field hypothesis* and the attention and charisma stories are not completely distinct in spirit, and perhaps interesting for many of the same reasons: In all three cases, the emergence of social executives brings in retail investors and improves stock market liquidity and retail investor participation.

Perhaps the key difference is that under the *grabbing investor attention story* or the *charisma story* executive tweets need not impart unique and value-relevant information. To this end, we reference our earlier evidence that (1) executive tweets provide unique and useful information regarding future operating performance, and that (2) our observed improvements in liquidity and retail investor base are much stronger when a social executive posts more value-relevant tweets.

We also conduct the following additional test: The presence of private information is typically accompanied with more active and short-term trading among investors privy to such private information; the absence of private information, in turn, generally comes with a more passive, buy-and-hold-type investment strategy (Fama 1991). If the emergence of social executives indeed causes some information previously privy to institutional investors to become available to the wider investor population, institutional investors should therefore lower their trading frequency. To empirically assess this possibility, for each firm with a social executive, we compute institutional investors' average holding period (in months) in the corresponding firm's shares in the one-year period prior to and after the corresponding firm's top executive becoming social.[32] As reported in Online Appendix Table 11, we find that prior to the emergence of a social executive, institutional investors' average holding period is 22.9 months. After the emergence, the average holding period lengthens to 27.4 months. The difference of 4.5 months is not only economically meaningful

[32] The holding period is the number of shares held by institutions, divided by the monthly number of shares traded by institutions.

but also statistically significant (*t*-statistic = 2.27).[33] Again, while we do not claim to be able to rule out completely the *grabbing investor attention story* or the *charisma story*, the above evidence is probably most easily understood within our leveling the playing field framework.

6. 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. We provide evidence that at least some top executive tweets contain novel and valuable information to investors. Unlike private meetings, which are reserved for the largest institutional investors, any investor can choose to follow any public Twitter account. The emergence of social executives thus marks a 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"[34] as such a common pool is thought to improve market quality and enhance economic growth (e.g., Levine and Zervos 1998; SEC 2018). In line with the notion that social executives can help create such a common pool and the idea that such a common pool improves market quality, we find evidence that the emergence of social executives has improved stock market liquidity and widened retail investor participation. Our evidence thus has strong regulatory implications. The relevance of our findings naturally extends to investors who may not yet be aware of the value-relevance of top executives' social media accounts, to social executives and executives considering becoming social, and to boards of directors monitoring and advising those executives.

In the end, there is no doubt that "social media is landscape-shifting."[35] We hope the results of our study help contribute to a balanced and informed discussion of how social media is continuously and importantly changing the manner in which financial market participants interact with one another.

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[33] In yet another attempt to gauge the relevance of our *leveling the playing field hypothesis*, we assess whether our results are stronger in cases where private meetings are more likely to create an uneven playing field. We explain and present these results in Online Appendix Table 12.

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

[35] https://www.sec.gov/about/offices/ocie/riskalert-socialmedia.pdf

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

Tweet	Tweet Date	Executive Name	Company Name
Panel A: "Type 1" Tweets: Company News			
Very excited about the prospects of the Sirius XM Satellite Radio App due to come out for iPhone users soon!	4/28/2009	Mel Karmazin	Sirius XM Holdings
AMN Revenue Up in Q4, Notes MSP Deals http://t.co/yVSZuGbP	3/9/2012	Susan R. Salka	AMN Healthcare Services
Amazing that Dell Boomi has averaged over 1 million Cloud integration processes per day for the past several... http://t.co/44QcqlMj	9/8/2012	Michael S. Dell	Dell
Western Union launches solution to deliver financial inclusion to millions in #India: prepaid cards.	10/23/2012	Hikmet Ersek	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	Dara Khosrowshahi	Expedia Group
RTI, United Technologies in titanium deal http://t.co/EXSGOQ4QFb	9/17/2013	Dawne S. Hickton	RTI International Metals
HMS Holdings welcomes Joel Portice and Doug Williams to our executive leadership team! http://t.co/y064qNoZ1q	12/9/2013	William C. Lucia	HMS Holdings Corp
Today we expanded our offer for Alstom to create an alliance in energy and transport, while preserving investor value http://t.co/tgRxzJ4Xja	6/19/2014	Jeffrey R. Immelt	General Electric
Major partnership announcement today between @VeriFone & @gilbarcoinc See the full announcement here http://t.co/h6LcGNBKS5	8/13/2014	Paul Galant	Verifone Systems
Unisys welcomes Virgin Atlantic to its SaaS-based Cargo Portal Services (CPS). http://t.co/MGmK5cVXqj	11/19/2014	J. Edward Coleman	Unisys Corp
Panel B: "Type 2" Tweets: Work-Related Day-to-Day Activities			
Just finished a meeting with a lot of good ideas about behavioral mapping ideas	5/7/2009	John P. McLaughlin	PDL BioPharma
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	John Heyman	Radiant Systems
Working on some exciting projects with the IDC (Independent Distributor Council) the next couple days.	11/13/2009	David A. Wentz	USANA Health Sciences
I have a new article on opensource.com: "Show me the money.." Please share your ideas. http://bit.ly/bDxIVL	5/24/2010	James M. Whitehurst	Red Hat
@Brylski Thanks for letting me know and thank you for shopping with us!	6/29/2011	Brian J. Dunn	Best Buy

Tweet	Tweet Date	Executive Name	Company Name
More depressed/upset than you've been in years? Try running an airline! -Dave Barger/CEO JetBlue	12/4/2012	David Barger	JetBlue Airways Corp
Nice Q&A about TripConnect - helping independent hotels connect with travelers. http://t.co/HX4y4Q4zNj	10/25/2013	Stephen Kaufer	Tripadvisor
Meeting with our partner and customer in Shanghai; Mr Chen Hong, President of SAIC. Helping me eat. http://t.co/Jik93eMMxZ	2/26/2014	Alex A. Molinaroli	Johnson Controls
WU believes in collaboration. We work closely w/ our NGO clients, tech providers & other experts 2 evolve our products 4 NGOs. #CGI2014	9/23/2014	Hikmet Ersek	Western Union
Great meeting today with the #Nutrisystem Science Advisory Board - #bestinclass Details: http://t.co/MpkGfHKHzJ #innovation	10/30/2014	Dawn M. Zier	Nutrisystem
Panel C: "Type 3" Tweets: Unrelated-to-Work Personal Interests and Moods			
Dinner at Hammersley's in Boston -this is still a great restaurant!!	10/23/2008	George F. Colony	Forrester Research
Enjoying drinks poolside with a nice fire with my wife, daughter and friends. Tonight life is good.	6/12/2009	Richard A. Meeusen	Badger Meter
Very disappointed that there will be no season 9 of 24!	3/27/2010	Michael S. Dell	Dell
Watching Ellen rerun with my all-girl family. Must be on vacation. Will play with army men later to reclaim masculinity.	8/11/2010	David P. Kirchhoff	Weight Watchers
In Europe on vac with family this week. Rome, now Venice - not sure I could live in a city with no cars, no bikes. Walking everywhere!	8/12/2010	Richard A. Meeusen	Badger Meter
Heading to the @AAarena for the BIG @MiamiHEAT OKC Thunder match-up. Tip is 8pm sharp be there loud & in Black.	4/4/2012	Micky M. Arison	Carnival Corp
Eric and I did 60 miles this morning. Time for a Starbucks and then the Ranger game. #LGR http://t.co/yWrcXSUW	5/12/2012	Mark T. Bertolini	Aetna
7 Qualities of Uber Productive People http://t.co/GIKhjj0	2/14/2013	Garry O. Ridge	WD-40
My ALS ice bucket challenge https://t.co/hTYgqViLJG	8/16/2014	Carl Bass	Autodesk
Boston would be a great choice for the 2024 Olympics! #2024olympics #Boston2024	12/15/2014	Shirley Singleton	Edgewater Technology

Figure 2. Variable Definitions

Variables	Definitions
Panel A: Table 3	
Earnings Surprise	The difference between the reported quarterly EPS and the average analyst EPS forecast, scaled by the stock price five trading days prior to the earnings announcement.
%Neg Executive Tweets	The average fraction of negative words across all tweets posted by the CEO/CFO from the most recent quarterly earnings announcement through the quarterly earnings announcement in question.
%Neg Executive Tweets _Firm	The analogue to *%Neg Executive Tweets* but based on Type 1 tweets only (tweets sharing company news); this variable is set to zero if there are no Type 1 tweets.
%Neg Executive Tweets _Work	The analogue to *%Neg Executive Tweets* but based on Type 2 tweets only (tweets describing work-related day-to-day activities); this variable is set to zero if there are no Type 2 tweets.
%Neg Executive Tweets_Personal	The analogue to *%Neg Executive Tweets* but based on Type 3 tweets only (tweets describing unrelated-to-work personal interests); this variable is set to zero if there are no Type 3 tweets.
Post SEC Embrace	An indicator that equals one if the observation is after April 2, 2013, and zero otherwise.
Log(1 + # Executive Tweets)	The natural logarithm of one plus the number of tweets posted by the CEO/CFO from the most recent quarterly earnings announcement through the quarterly earnings announcement in question.
Log(1 + # Company Tweets)	The natural logarithm of one plus the number of tweets posted by the company-managed Twitter account from the most recent quarterly earnings announcement through the quarterly earnings announcement in question.
%Neg Company Tweets	The average fraction of negative words across *Company Tweets*; this variable is set to zero if *#Company Tweets* is zero.
Log(1 + # Company FB Posts)	The natural logarithm of one plus the number of Facebook posts from the company Facebook page from the most recent quarterly earnings announcement through the quarterly earnings announcement in question.
%Neg Company FB Posts	The average fraction of negative words across *Company FB Posts*; this variable is set to zero if *#Company FB Posts* is zero.
Log(1 + # DJNS Articles)	The natural logarithm of one plus the number of articles published in the DJNS about the corresponding firm from the most recent quarterly earnings announcement through the quarterly earnings announcement in question.
%Neg DJNS Articles	The average fraction of negative words across *DJNS Articles*; this variable is set to zero if *#DJNS Articles* is zero.
Log(1 + # Seeking Alpha Articles)	The natural logarithm of one plus the number of articles published on Seeking Alpha about the corresponding firm from the most recent quarterly earnings announcement through the quarterly earnings announcement in question.
%Neg Seeking Alpha Articles	The average fraction of negative words across *Seeking Alpha Articles*; this variable is set to zero if *#Seeking Alpha Articles* is zero.

Variables	Definitions
Log(1 + # Seeking Alpha Comments)	The natural logarithm of one plus the number of Seeking Alpha comments in response to Seeking Alpha articles about the corresponding firm from the most recent quarterly earnings announcement through the quarterly earnings announcement in question.
%Neg Seeking Alpha Comments	The average fraction of negative words across *Seeking Alpha Comments*; this variable is set to zero if *#Seeking Alpha Comments* is zero.
Forecast Dispersion	The standard deviation of analysts' earnings forecasts for the quarterly earnings announcement in question, scaled by lagged stock price.
Forecast Revision	The change in the analyst consensus forecast for the quarterly earnings announcement from right after the most recent quarterly earnings announcement to right before the quarterly earnings announcement in question.
Log(Size)	The natural logarithm of the market value of equity at the end of the preceding calendar year.
Book-to-Market	The book value of equity divided by the market value of equity at the end of the preceding calendar year.
Share Turnover	The number of shares traded in the previous year, scaled by the number of shares outstanding at the end of the preceding calendar year.
$Aret_{-2}$	Abnormal return on trading day -2 prior to the quarterly earnings announcement in question. Abnormal returns are market-adjusted returns.
$Aret_{-30,-3}$	Cumulative abnormal return over the (-30,-3) trading day period prior to the quarterly earnings announcement in question. Abnormal returns are market-adjusted returns.
$Aret_{-225,-31}$	Cumulative abnormal return over the (-225,-31) trading day period prior to the quarterly earnings announcement in question. Abnormal returns are market-adjusted returns.

Panel B: Tables 4, 5, and 6 (When dependent variable is *Spread*, *Log(Depth)*, or *Turnover*, *t* represents days; otherwise, *t* represents years)	
Spread	The daily percentage spread as detailed in Section 3.2.1.
Log(Depth)	The natural logarithm of the daily depth as detailed in Section 3.2.1.
Retail Turnover	The daily number of shares traded by retail investors, divided by the number of shares outstanding (as detailed in Section 3.2.1).
Inst. Turnover	The daily number of shares traded by institutional investors, divided by the number of shares outstanding (as detailed in Section 3.2.1).
Log(#Retail Investors)	The natural logarithm of the total number of shareholders minus the number of institutional investors [in thousands].
Log(#Inst. Investors)	The natural logarithm of the number of institutional investors.

Variables	Definitions
TreatmentGroup	An indicator that equals one if the corresponding firm belongs to the treatment group (the firm has or will have a social executive) and zero otherwise.
AfterBecomingSocial	An indicator that equals one if the CEO/CFO has been tweeting as of time *t* and zero otherwise.
Log(1 + # CompanyTweets)	The natural logarithm of one plus the number of tweets posted by the company-managed Twitter account at time *t*.
%Neg Company Tweets	The average fraction of negative words across *Company Tweets*; this variable is set to zero if *#Company Tweets* is zero.
Log(1 + # Company FB Posts)	The natural logarithm of one plus the number of Facebook posts from the company Facebook page at time *t*.
%Neg Company FB Posts	The average fraction of negative words across *Company FB Posts*; this variable is set to zero if *#Company FB Posts* is zero.
Log(1 + # DJNS Articles)	The natural logarithm of one plus 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 *DJNS Articles*; this variable is set to zero if *#DJNS Articles* is zero.
Log(1 + # Seeking Alpha Articles)	The natural logarithm of one plus 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 *Seeking Alpha Articles*; this variable is set to zero if *#Seeking Alpha Articles* is zero.
Log(1 + #Seeking Alpha Comments)	The natural logarithm of one plus the number of Seeking Alpha comments in response to Seeking Alpha articles about the corresponding firm at time *t*.
%Neg Seeking Alpha Comments	The average fraction of negative words across *Seeking Alpha Comments*; this variable is set to zero if *#Seeking Alpha Comments* is zero.
Earnings Announcement	An indicator that equals one if the corresponding firm announces earnings at time *t.*
Log(1 + #Analysts)	The natural logarithm of one plus the number of analysts issuing an earnings forecast for the most recent quarterly earnings announcement.
Inst. Holdings	The fraction of shares held by institutional investors as of the most recent calendar quarter end.
Abs. Abn. Ret	The absolute value of the difference between a firm's return and the value-weighted return of all firms in the CRSP sample at time *t.*
Share Turnover	The daily number of shares traded, scaled by the number of shares outstanding.
Size	The firm's market value of equity in millions at time.
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) at time *t*.

Variables	Definitions
Log(Asset)	The natural logarithm of total assets as of the previous fiscal-quarter end.
Log(Price)	The natural logarithm of the firm's stock price at time *t*.
Monthly Volatility	The standard deviation of the firm's daily stock returns in the previous calendar month.
Log(#Shareholders)	The natural logarithm of the total number of shareholders as of the most recent fiscal-quarter end.
IMR	We estimate a Twitter-adoption prediction model for each year from 2008 to 2014 by regressing the Twitter adoption statuses in a year on a set of explanatory variables. 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(Fewer) # Tweets	An indicator that equals one if the CEO/CFO's average number of tweets in the first year of the Twitter activation is above (below) the sample median, and zero otherwise.
More(Fewer) # Re-tweets	An indicator that equals one if the CEO/CFO's average number of re-tweets in the first year of the Twitter activation is above (below) the sample median, and zero otherwise.
More(Fewer) # Followers	An indicator that equals one if the CEO/CFO's total number of followers at the end of our sample period is above (below) the sample median, and zero otherwise.
More(Fewer) %Work-Related Tweets	An indicator that equals one if the CEO/CFO's (*Firm* + *Work*)/(*Firm* + *Work* + *Personal*) tweets in the first year of the Twitter activation is above (below) the sample median, and zero otherwise, where *Firm*/*Work*/*Personal* is the number of company news/work-related day-to-day activities/ unrelated-to-work personal interests tweets posted by the CEO/CFO.
Firm with Social Executive *pre SEC Embrace*	An indicator that equals one if a firm has a social executive prior to April 2, 2013 and zero otherwise.
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"

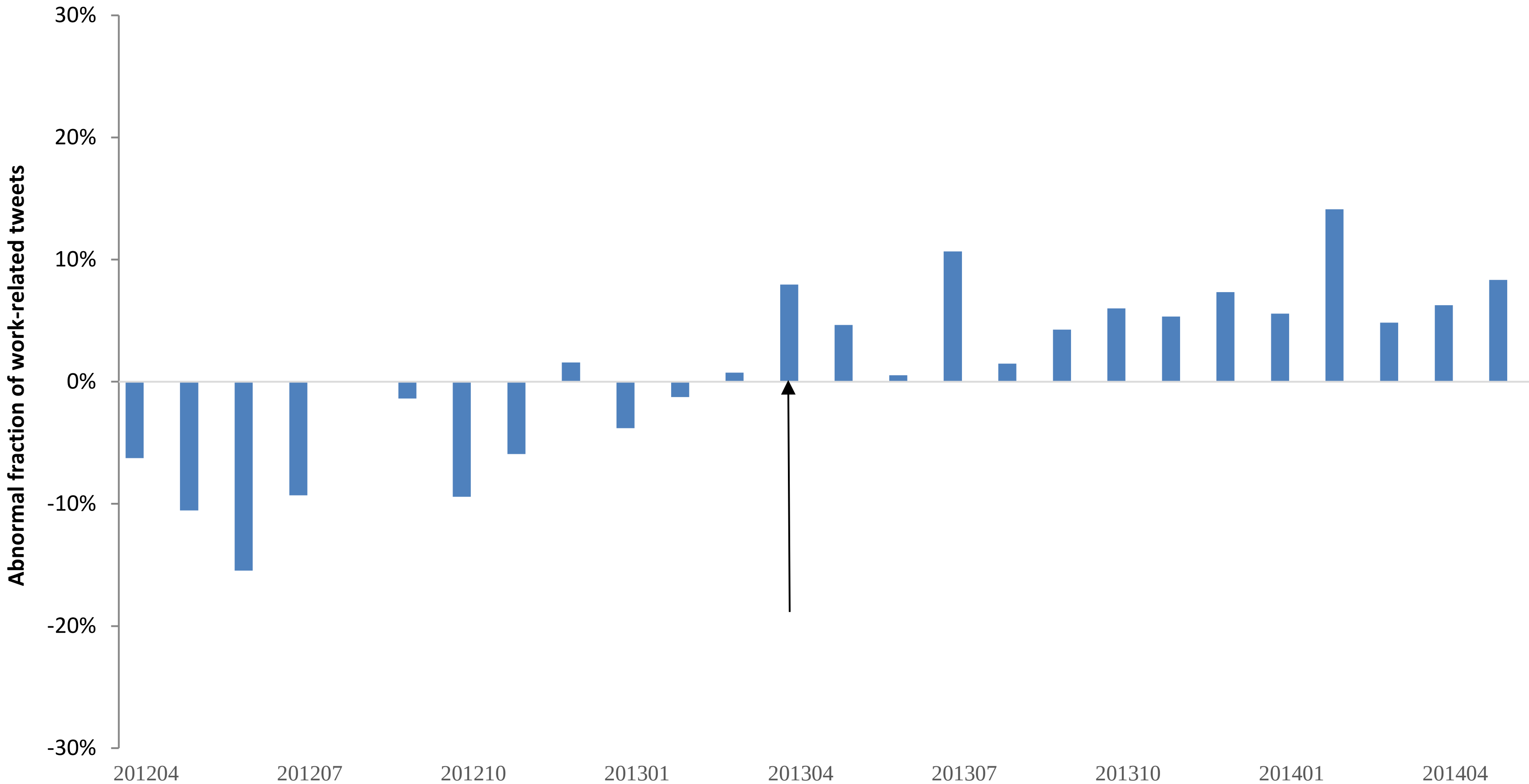

Table 1. Descriptive Statistics on Twitter Activity

	Total # of Social Executives	Total # of Firms with Social Executives	Total # of Tweets	Total # of Tweets / Firm
Panel A: 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
All Years	155	141	47,119	331.82
Panel B: 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
Panel C: Executive Type				
CEO	117	116	44,586	386.69
CFO	38	37	2,533	68.46
Panel D: Executive Gender				
Male	142	130	45,233	347.95
Female	13	12	1,886	157.17

Table 2. Descriptive Statistics on Firm Characteristics and Regression Variables

	N	Mean	Std. Dev	25th Pctl	50th Pctl	75th Pctl
Panel A: Sample of "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%
Institutional Holding	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 Shareholders (thousands)	994	17.74	70.80	0.06	1.23	8.54
#Institutional Shareholders	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%
Institutional Holding	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 Shareholders(thousands)	11,652	27.68	855.07	0.04	1.20	8.36
#Institutional Shareholders	11,652	260	246	119	176	312
Panel C: Variables used in Table 3						
Earnings Surprise [%]	1,790	0.03	7.70	-0.41	0.06	0.48
%Neg Executive Tweets [%]	1,790	0.53	1.34	0.00	0.62	1.69
%Neg Executive Tweets_Firm [%]	1,790	0.29	1.02	0.00	0.09	0.85
%Neg Executive Tweets_Work [%]	1,790	0.22	0.83	0.00	0.00	0.67
%Neg Executive Tweets_Personal [%]	1,790	0.02	0.26	0.00	0.00	0.37
# Executive Tweets	1,790	22.31	56.96	0.00	1.00	15.00
# Company Tweets	1,790	380.55	1493.76	0.00	105.00	319.00
%Neg Company Tweets [%]	1,790	0.57	0.79	0.00	0.43	0.79
# Company FB Posts	1,790	60.93	78.48	0.00	25.00	104.00
%Neg Company FB Posts	1,790	0.50	0.90	0.00	0.28	0.75
# DJNS Articles	1,790	8.24	18.13	0.00	3.00	9.00
%Neg DJNS Articles [%]	1,790	0.67	0.82	0.00	0.43	1.06
# Seeking Alpha Articles	1,790	4.02	12.67	0.00	0.00	2.00
%Neg Seeking Alpha Articles [%]	1,790	0.37	0.60	0.00	0.00	0.64
# Seeking Alpha Comments	1,790	73.68	552.87	0.00	3.00	41.00
%Neg Seeking Alpha Comments [%]	1,790	0.34	0.76	0.00	0.34	1.31
Forecast Dispersion[%]	1,790	4.31	7.33	1.47	2.39	3.98
Forecast Revisions[%]	1,790	-0.01	0.73	-0.01	0.00	0.01
Size (in billions)	1,790	16.89	53.15	0.58	1.46	6.68
Book-to-market	1,790	0.47	0.50	0.21	0.41	0.68
Share Turnover	1,790	2.67	1.74	1.36	2.38	3.56
$Aret_{-2}$ [%]	1,790	0.07	2.07	-0.84	0.01	0.98
$Aret_{-30,-3}$ [%]	1,790	0.15	11.17	-5.30	-0.17	5.03
$Aret_{-225,-31}$ [%]	1,790	5.90	32.91	-13.75	3.68	23.67

	N	Mean	Std. Dev	25th Pctl	50th Pctl	75th Pctl
Panel D: Variables used in Table 4						
Spread [%]	91,805	0.08	0.61	0.01	0.02	0.06
Depth (in thousands)	91,805	63.08	133.44	11.38	22.42	51.53
Retail Turnover [%]	91,805	0.08	0.24	0.02	0.04	0.08
Inst. Turnover [%]	91,805	0.33	0.76	0.09	0.17	0.33
# Retail Investors (in thousands)	1,306	47.55	216.67	0.20	1.84	11.91
# Inst. Investors	1,306	277.36	300.59	114.00	173.00	330.50
# Company Tweets	91,805	2.68	18.90	0.00	1.00	6.00
%Neg Company Tweets	91,805	0.24	1.04	0.00	0.47	1.58
# Company FB Posts	91,805	0.50	2.01	0.00	2.00	3.00
%Neg Company FB Posts	91,805	0.20	1.42	0.00	0.00	1.00
# DJNS Articles	91,805	0.11	0.58	0.00	1.00	2.00
%Neg DJNS Articles	91,805	0.09	0.48	0.00	0.16	0.28
# Seeking Alpha Articles	91,805	0.13	0.33	0.00	1.00	1.00
%Neg Seeking Alpha Articles	91,805	0.01	0.06	0.00	0.02	0.03
# Seeking Alpha Comments	91,805	0.11	3.28	0.00	1.00	1.00
%Neg Seeking Alpha Comments	91,805	0.02	0.06	0.00	0.04	0.05
Earnings Announcement	91,805	0.01	0.11	0.00	0.00	1.00
# Analysts	91,805	8.11	9.03	1.00	5.00	12.00
Institutional Holding	91,805	0.75	0.22	0.64	0.80	0.92
Abs. Abn. Ret [%]	91,805	1.69	2.71	0.43	0.99	2.00
Share Turnover [%]	91,805	1.12	1.51	0.46	0.79	1.35
Size (in billions)	91,805	7.45	1.90	6.29	7.31	8.63
Book-to-market	91,805	1.04	2.94	0.28	0.51	0.89
Asset (in billions)	91,805	14.32	54.06	0.67	2.14	7.26
Price	91,805	31.60	46.29	10.87	23.13	37.66
Monthly Volatility [%]	91,805	2.14	1.85	1.07	1.63	2.55
# of Shareholders	91,805	41.51	177.75	0.48	2.03	13.07
IMR	91,805	2.50	0.53	2.09	2.53	2.99
Panel E: Twitter Account Characteristic Variables used in Table 5						
# Tweets	141	77.88	202.14	8.50	64.00	178.00
# Followers (in thousands)	141	40.14	190.17	0.12	1.14	10.93
# Re-tweets (in thousands)	141	26.26	280.43	0.02	0.12	3.52
# Firm Tweets	141	3.02	10.03	0.00	2.00	6.00
# Work Tweets	141	48.76	125.71	1.00	5.50	35.00
# Personal Tweets	141	46.88	144.69	1.00	8.50	40.00
%Work-Related Tweets	141	0.50	0.38	0.06	0.45	0.86

Notes: (1) the observations in Panels A and B are at the firm/year level from 2008 through 2014; (2) the observations in Panels C and D comprise all the observations used in the regressions tabulated in Table 4; (3) the observations in Panel E are at the social executive level and represent Twitter account characteristics as of the end of the first year of the Twitter account activation.

Table 3. Information Content in Top Executives' Tweets

	Earnings Surprise [%]		
	(1)	(2)	(3)
%Neg Executive Tweets	-0.105*** (-2.83)	-0.029** (-2.34)	
%Neg Executive Tweets_Firm			-0.040 (-0.20)
%Neg Executive Tweets _Work			-0.230*** (-2.92)
%Neg Executive Tweets_Personal			0.036 (0.24)
Post SEC Embrace		-0.125 (-1.37)	
*%Neg Executive Tweets * Post SEC Embrace*		-0.140** (-2.59)	
Log(1 + # Executive Tweets)	-0.000 (-0.19)	-0.000 (-0.23)	-0.000 (-0.08)
Log(1 + # Company Tweets)	-0.001 (-0.71)	-0.001 (-0.71)	-0.001 (-0.68)
%Neg Company Tweet	-0.138 (-1.09)	-0.150 (-1.19)	-0.148 (-1.14)
Log(1 + # Company FB Posts)	-0.000 (-0.42)	-0.000 (-0.42)	-0.000 (-0.46)
%Neg Company FB Posts	0.006 (0.04)	-0.003 (-0.02)	0.006 (0.04)
Log(1 + # DJNS Articles)	0.003 (0.89)	0.003 (0.87)	0.003 (0.88)
%Neg DJNS Articles	-0.374** (-2.14)	-0.382** (-2.16)	-0.372** (-2.13)
Log(1 + # Seeking Alpha Articles)	0.003 (0.59)	0.002 (0.49)	0.003 (0.62)
%Neg Seeking Alpha Articles	-0.267 (-0.62)	-0.279 (-0.64)	-0.266 (-0.62)
Log(1 + # Seeking Alpha Comments)	-0.001 (-0.67)	-0.001 (-0.57)	-0.002 (-0.72)
%Neg Seeking Alpha Comments	0.116 (0.66)	0.114 (0.65)	0.114 (0.64)
Forecast Dispersion	-0.065 (-1.04)	-0.066 (-1.06)	-0.066 (-1.04)
Forecast Revisions	1.202*** (5.04)	1.197*** (5.01)	1.203*** (5.04)
Log(Size)	-0.001 (-0.48)	-0.001 (-0.41)	-0.001 (-0.47)
Book-to-market	-0.014*** (-2.54)	-0.014*** (-2.51)	-0.014*** (-2.53)
Share Turnover	-0.001 (-0.85)	-0.001 (-0.95)	-0.001 (-0.83)

	Earnings Surprise [%]		
	(1)	(2)	(3)
$ARet_{-2}$	-0.134	-0.133	-0.134
	(-1.04)	(-1.03)	(-1.04)
$ARet_{-30,-3}$	0.095**	0.094**	0.095**
	(2.34)	(2.32)	(2.35)
$ARet_{-252,-31}$	0.026***	0.026***	0.026***
	(3.85)	(3.88)	(3.86)
# Obs.	1,790	1,790	1,790
Adj. R^2	0.091	0.093	0.090

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

Table 4. The Effects of Twitter Adoption on Liquidity and Investor Base

	Spread [%]	Log(Depth)	Retail Turnover [%]	Inst. Turnover [%]	Log(#Retail Investors)	Log(#Inst. Investors)
	(1)	(2)	(3)	(4)	(5)	(6)
TreatmentGroup × AfterBecomingSocial	-0.027***	0.023***	0.010***	0.004	0.105**	0.028
	(-4.31)	(4.78)	(3.69)	(0.50)	(2.77)	(1.21)
Log(1 + # CompanyTweets)	-0.003	0.008***	-0.005***	-0.006	-0.023	0.005
	(-0.90)	(3.94)	(-3.29)	(-1.28)	(-0.95)	(0.87)
%Neg Company Tweet	0.025	-0.006	-0.040	0.003	18.243	-3.674
	(0.11)	(-0.06)	(-1.03)	(0.02)	(1.56)	(-1.70)
Log(1 + # Company FB Posts)	0.007	0.008**	-0.002	-0.007	-0.001	0.004
	(1.14)	(2.41)	(-1.46)	(-1.46)	(-0.03)	(0.74)
%Neg Company FB Posts	-0.060	0.158**	0.059*	0.316**	2.629	-3.566**
	(-0.36)	(2.41)	(1.74)	(2.12)	(0.32)	(-2.29)
Log(1 + # DJNS Articles)	0.004	-0.018***	0.051***	0.188***	-0.017	-0.026*
	(0.21)	(-2.94)	(4.84)	(4.98)	(-0.53)	(-2.09)
%Neg DJNS Articles	-0.337	0.287	-0.386	-1.293	2.588	2.293**
	(-0.50)	(1.06)	(-1.02)	(-1.02)	(0.56)	(2.57)
Log(1 + # Seeking Alpha Articles)	-0.235	0.007	-0.014	-0.176**	0.193	-0.317
	(-1.02)	(0.08)	(-0.50)	(-1.94)	(1.07)	(-1.62)
%Neg Seeking Alpha Articles	4.948	1.534	1.064	4.589	-0.707	2.313
	(0.37)	(0.36)	(0.67)	(1.39)	(-0.19)	(1.23)
Log(1 + #Seeking Alpha Comments)	0.517	0.076	0.024	0.166	-0.486**	0.370
	(1.11)	(0.85)	(0.86)	(1.53)	(-2.21)	(1.57)
%Neg Seeking Alpha Comments	7.182	-2.108	-1.631**	-5.458**	2.806	-1.901
	(0.40)	(-1.19)	(-2.26)	(-2.32)	(1.41)	(-1.01)
Earnings Announcement	-0.002	-0.056***	0.016***	0.136***		
	(-0.34)	(-4.81)	(2.53)	(4.49)		
Log(1 + #Analysts)	-0.048***	0.030***	0.003**	0.024***	0.031	0.066
	(-8.46)	(9.56)	(1.97)	(2.91)	(0.32)	(1.65)
Institutional Holding	0.043	0.359***	-0.018*	0.151***		
	(0.85)	(10.90)	(-1.70)	(3.12)		
Abs. Abn. Ret	0.093*	-0.071	2.172***	6.862***	-0.063	-0.068**
	(1.78)	(-0.56)	(11.24)	(14.27)	(-1.56)	(-2.49)

	Spread [%]	Log(Depth)	Retail Turnover [%]	Inst. Turnover [%]	Log(#Retail Investors)	Log(#Inst. Investors)
	(1)	(2)	(3)	(4)	(5)	(6)
Share Turnover	-0.063	5.400***			3.913*	2.557***
	(-0.54)	(10.97)			(1.97)	(3.62)
Size	0.267***	0.475***	0.011	0.020	-0.034	0.242***
	(4.03)	(19.16)	(1.60)	(0.83)	(-0.21)	(7.40)
Book-to-market	0.002***	-0.002	0.003*	0.002	0.002	0.001
	(2.79)	(-0.84)	(1.70)	(0.29)	(1.15)	(1.17)
Log(Asset)	-0.002	0.158***	-0.020***	-0.075***	0.058*	-0.007*
	(-0.14)	(9.04)	(-3.24)	(-4.00)	(1.90)	(-1.80)
Log(Price)	-0.268***	-0.178***	0.030***	0.095***	0.099	-0.095***
	(-3.91)	(-7.27)	(4.85)	(4.05)	(0.70)	(-4.12)
Monthly Volatility	0.027	0.333	0.966***	2.136***	0.107	-0.541
	(0.30)	(1.42)	(7.83)	(4.80)	(0.05)	(-0.48)
Log(# of Shareholders)	0.011*	0.074***	0.002	-0.001		
	(1.77)	(6.45)	(0.62)	(-0.05)		
IMR	0.014***	0.005	-0.001	0.012**	0.039	-0.004
	(3.03)	(1.20)	(-0.43)	(2.22)	(0.23)	(-0.21)
# Obs.	91,805	91,805	91,805	91,805	1,306	1,306
Adj. R^2	0.255	0.925	0.390	0.542	0.931	0.951

Notes: (1) firm and year-month-day fixed effects are included in Columns (1) through (4) and firm and year fixed effects are included in Columns (5) and (6); (2) in Columns (1) through (4), *t*-statistics are computed using standard errors clustered by both firm and year-month-day and are reported in parentheses; (3) in Columns (5) and (6), *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 5. The Effects of Twitter Adoption on Liquidity and Investor Base: Account Characteristics as a Moderator

Coefficient estimate for *TreatmentGroup* × *AfterBecomingSocial* within the subsample of social executives who …	Spread [%] (1)	Log(Depth) (2)	Retail Turnover [%] (3)	Inst. Turnover [%] (4)	Log(#Retail Investors) (5)	Log(#Inst. Investors) (6)
Panel A. # Re-tweets						
… have more # re-tweets	-0.064***	0.052***	0.018***	0.007	0.451**	0.082*
	(-8.65)	(6.17)	(4.37)	(0.99)	(2.73)	(1.95)
… have fewer # re-tweets	-0.013	0.011**	-0.002	0.006	-0.071	-0.016
	(-1.02)	(2.01)	(-0.65)	(0.52)	(-0.46)	(-0.83)
Panel B. # Followers						
… have more # followers	-0.065***	0.030***	0.021***	-0.063	0.161**	0.027
	(-8.60)	(5.17)	(5.48)	(-0.54)	(2.13)	(0.59)
… have fewer # followers	-0.013	0.024***	0.017***	0.030	0.090	-0.001
	(-0.79)	(2.70)	(5.64)	(0.25)	(0.55)	(-0.03)
Panel C. # Tweets						
… post more # tweets	-0.062***	0.057***	0.023***	-0.023	0.180**	0.052
	(-7.26)	(7.26)	(5.07)	(0.72)	(2.38)	(1.44)
… post fewer # tweets	-0.003	0.004	0.008***	0.028	0.022	-0.002
	(-0.33)	(0.63)	(3.87)	(0.37)	(0.11)	(-0.09)
Panel D. Fraction of Tweets that are Work-Related						
… have more % work-related tweets	-0.126***	0.039***	0.012***	0.011	0.089***	0.067
	(-10.52)	(6.39)	(3.35)	(1.53)	(2.91)	(1.60)
… have fewer % work-related tweets	-0.046***	0.007	0.010*	0.002	0.072	-0.033
	(-4.95)	(0.90)	(1.72)	(0.13)	(0.30)	(-1.24)

Notes: (1) firm and year-month-day fixed effects are included in Columns (1) through (4) and firm and year fixed effects are included in Columns (5) and (6); (2) in Columns (1) through (4), *t*-statistics are computed using standard errors clustered by both firm and year-month-day and are reported in parentheses; (3) in Columns (5) and (6), *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 Effect of the SEC's Embrace of Social Media

	Bid-Ask Spread [%]	Log(Depth)	Retail Turnover [%]	Inst. Turnover [%]	Log(#Retail Investors)	Log(#Inst. Investors)
	(1)	(2)	(3)	(4)	(5)	(6)
Firm with Social Executive$_{pre\ SEC\ Embrace}$	-0.062***	0.138***	0.026**	0.033	0.117**	-0.101
× Post SEC Embrace	(-7.10)	(11.13)	(1.97)	(0.60)	(2.34)	(-1.49)
Log(1 + # CompanyTweets)	-0.019***	0.006**	-0.002	0.009	-0.033	0.007
	(-2.50)	(2.07)	(-0.89)	(1.35)	(-0.54)	(0.89)
%Neg Company Tweets	-0.017	-0.130	-0.010	-0.082	22.161	-4.693*
	(-0.04)	(-1.00)	(-0.18)	(-0.45)	(1.08)	(-1.83)
Log(1 + # Company FB Posts)	0.022	0.019***	0.002	-0.005	-0.010	0.004
	(1.49)	(3.65)	(0.83)	(-0.89)	(-0.19)	(0.41)
%Neg Company FB Posts	-0.072	0.210***	-0.033	-0.049	12.896	-4.445
	(-0.27)	(2.73)	(-0.70)	(-0.61)	(1.20)	(-1.22)
Log(1 + # DJNS Articles)	0.011	0.002	0.016**	0.094**	-0.050	-0.018
	(0.37)	(0.33)	(2.40)	(1.96)	(-0.92)	(-0.70)
%Neg DJNS Articles	0.053	0.186	0.783	0.369	9.197	1.367
	(0.03)	(0.48)	(1.59)	(0.20)	(1.36)	(0.87)
Log(1 + # Seeking Alpha Articles)	-0.616	-0.005	0.001	-0.063	0.288	-0.293
	(-1.33)	(-0.06)	(0.03)	(-0.27)	(1.58)	(-1.09)
%Neg Seeking Alpha Articles	7.206	-3.861	-0.721	0.699	-1.564	2.088
	(0.31)	(-1.26)	(-0.76)	(0.23)	(-0.48)	(0.85)
Log(1 + #Seeking Alpha Comments)	0.910	0.199**	-0.005	-0.008	-0.666	0.363
	(1.54)	(2.03)	(-0.13)	(-0.03)	(-1.48)	(1.04)
%Neg Seeking Alpha Comments	-4.561	-3.113	-0.035	0.151	4.447*	-1.716
	(-0.21)	(-0.87)	(-0.08)	(0.08)	(1.77)	(-0.70)
Earnings Announcement	0.006	-0.040**	-0.006	0.075		
	(0.40)	(-1.97)	(-0.35)	(1.53)		
Log(1 + #Analysts)	-0.143***	0.041***	-0.000	0.021	0.112	0.090**
	(-10.09)	(8.41)	(-0.00)	(1.27)	(1.05)	(1.93)
Institutional Holding	-0.050	0.103***	-0.043***	-0.007		
	(-0.43)	(2.60)	(-2.55)	(-0.09)		
Abs. Abn. Ret.	0.578**	0.525***	3.971***	10.537***	-0.048	-0.063**
	(2.34)	(3.05)	(9.22)	(15.77)	(-0.67)	(-2.04)

	Spread [%]	Log(Depth)	Retail Turnover [%]	Inst. Turnover [%]	Log(#Retail Investors)	Log(#Inst. Investors)
	(1)	(2)	(3)	(4)	(5)	(6)
Share Turnover	-0.860**	4.743***			6.291	2.077***
	(-2.14)	(8.16)			(1.22)	(2.65)
Size	0.577***	0.428***	-0.031***	-0.061***	-0.280	0.232***
	(4.18)	(13.60)	(-2.85)	(-2.60)	(-1.12)	(4.17)
Book-to-market	0.027***	-0.011	-0.007	-0.017	0.003	0.001
	(4.25)	(-1.33)	(-1.06)	(-0.53)	(1.11)	(1.40)
Log(Asset)	0.036	0.017	-0.003	-0.059**	0.073	-0.011*
	(0.62)	(0.68)	(-0.34)	(-1.98)	(1.13)	(-1.71)
Log(Price)	-0.531***	-0.239***	0.021***	0.077***	0.339	-0.098*
	(-3.76)	(-8.05)	(3.21)	(4.30)	(1.53)	(-1.88)
Volatility	0.763*	0.622**	0.393	1.104***	-0.136	-0.540
	(1.74)	(2.19)	(1.55)	(2.64)	(-0.03)	(-0.58)
Log(# of Shareholder)	0.203***	-0.051***	-0.033***	-0.040		
	(5.78)	(-3.62)	(-3.30)	(-1.21)		
IMR	0.058***	0.006	0.001	0.021***	0.148	0.001
	(4.41)	(0.89)	(0.48)	(2.80)	(0.77)	(0.03)
# Obs.	29,987	29,987	29,987	29,987	1,032	1,032
Adj. R^2	0.228	0.930	0.426	0.553	0.919	0.946

Notes: (1) firm and year-month-day fixed effects are included in Columns (1) through (4) and firm and year fixed effects are included in Columns (5) and (6); (2) in Columns (1) through (4), *t*-statistics are computed using standard errors clustered by both firm and year-month-day and are reported in parentheses; (3) in Columns (5) and (6), *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.