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Messaging without a message: executive value and social media activity

Ru GAO

Gilles HILARY

Rencheng WANG
Singapore Management University, rcwang@smu.edu.sg

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Ru (Tina) Gao
The University of Queensland
r.gao@business.uq.edu.au

Gilles Hilary
Georgetown University
gilles.hilary@georgetown.edu

Rencheng Wang
The University of Melbourne
rencheng.wang@unimelb.edu.au

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Messaging without a Message: Executive Value and Social Media Activity

Abstract

We show that executives who start tweeting benefit from better career options. We motivate this finding using the well-established theory of limited attention. Consistent with this explanation, we find that content is irrelevant. Comparative statics are also consistent with our framework. In particular, the effect of Twitter is greater for executives who were largely unrecognized and who were underpaid before they started tweeting, who garner greater public attention from their social media activity, who enjoy higher professional mobility, and who operate in environments where compensation setting is less structured.

Key words: limited attention; social media; Twitter

JEL: G02; J01; J30; M51; O35

I. Introduction

What drives the market value of executives and their compensation? Traditionally, the literature has suggested two basic explanations. The first postulates that managerial labor markets are largely efficient and that managerial compensation reflects executive marginal value. In contrast, the rent-seeking view posits that executives, CEOs in particular, are able to entrench themselves in their organizations and, once they have reached this objective, are able to extract compensation that goes beyond their marginal contribution. Empirically, prior research supports both views. On average, executive compensation appears to reflect managerial contribution, but this relation breaks down in firms in which corporate governance is weak (e.g., Chang, Dasgupta, and Hilary 2010). In both frameworks, managerial quality is reasonably well-observed and, absent material governance issues, is reflected in executive contracts. In particular, there is no *a priori* reason for executives to receive compensation below their marginal product.

We rely on behavioral literature and more specifically on theories of limited attention to propose a third framework that complements the previous two. Limited attention is the idea that humans confront a great wealth of signals that are costly to process. There is a limit to the amount of information contracting parties can process, and therefore salient information receives disproportionate attention. Psychology literature (e.g., Kahneman 1973; Fiske and Taylor 1991) has shown that these two cognitive biases matter in individual decision making. Economists have also built on these concepts. For example, Camerer (2003) lists limited attention as an important topic for behavioral economics. Gabaix (2017) considers it to be a central, unifying theme for much of behavioral economics. Given that individuals have limited attention to fully inspect the properties of goods and services, it is natural to expect their valuation to be inaccurate at times. Most of the literature on this topic focuses on asset pricing considerations, showing how investors underreact to some information but overreact to other information (e.g., Huberman and Regev 2001; Corwin and Coughenour 2008). Parallel literature in accounting demonstrates how firms can exploit these effects (e.g., Hirshleifer and Teoh 2003; Hirshleifer, Lim, and Teoh 2004).

We expect human capital to be similarly mispriced. The executive labor market is broad, and the marginal contribution of an executive is difficult to ascertain (e.g., Holmstrom 1982; Wade, O'Reilly, and Pollock 2006). Thus, we expect that perceptions and heuristics are important factors when boards decide which executives they want to attract and retain. In particular, when faced with limited attention capacity and complex choices, employers are likely to favor individuals with more prominent profiles. Consequently, executives who are unable to generate sufficient public attention may be undervalued, even if they perform well objectively. Conversely, saliency has been shown to affect the value of items that are bought and sold. Thus, we expect the market value of an executive to increase when there is greater public awareness of her existence, in part because this increased notoriety should lead to better outside options for her. In other words, we hypothesize that creating greater notoriety beyond current employers gives executives more leverage in their current positions. We also predict the benefit to be concentrated among executives who are underappreciated (before engaging in social media activity), among individuals who are able to move to other organizations, and in settings in which executive searches are less systematic.

Our results support our predictions. Specifically, we use the executive's personal tweeting activity as a source of variation in the public attention to identify the effect of limited attention on executive value. First, we find that initiating personal tweeting activity increases executive compensation, even after controlling for variations in firm performance and value. The benefits are stronger when managers enjoy more followers, and when these followers are more focused (i.e., follow a small number of other Twitter accounts). Our findings are robust to different alternative empirical specifications and methods. In particular, our conclusions are not affected by (1) various instrumental variable approaches, (2) different matched sample approaches, (3) a parallel trend analysis, and (4) several panel specifications that control for time-invariant and slow-moving characteristics (such as executive ability or psychological characteristics). The results also hold when we control for both personal and firm media coverage, the size of the personal social network "in real life" (obtained through employment, education, and other activities), firm transparency, governance, and for presence on other personal social media platforms (e.g., Facebook and LinkedIn). A Monte Carlo placebo test suggests an omitted variable would have to be extremely correlated with our treatment variable to explain our results.

Importantly, our comparative statics are consistent with the limited attention framework in several ways. First, the positive effect of Twitter is the greatest for managers who are not well known before initiating tweeting activity, such as those who are not CEOs, who are infrequently researched on Google, or who were recently appointed as executives. In other words, the benefit of tweeting is greatest in samples where we expect the demand for attention to be highest. Second, we show that executives who use attention-enhancing techniques benefit more from their social media activity. For example, managers who tweet more frequently, facilitate retweeting (by using hashtags in their posts), and use directed tweets (i.e., tweets that use the @ function to link with high-profile accounts) derive greater benefit from their activity.

Aside from establishing the baseline results, we find that managers are able to garner better career options but that this effect is more significant when executive searches are less systematic and focused. First, the effect of Twitter is concentrated in executives who are underpaid (compared with their peers) before engaging in Twitter activity. However, the benefit of tweeting disappears when the low compensation is the consequence of systematic benchmarking. For example, the benefit of tweeting is lower for executives who work for companies that use compensation consultants. Also consistent with the notion that attention matters, the benefits of tweeting are greater when board members are "busier" (and do not use consultants). These samples without clear benefits suggest that not all executives have incentives to tweet. Second, executives who start tweeting secure better outside options. For example, they sit on more boards outside their current employer. Consistent with the notion that systematic searches weaken the benefit of tweeting, these new positions are concentrated among private companies, where searches are more likely to be ad hoc and more subject to attention biases. However, the internal benefits of tweeting are limited to executives who are professionally mobile (i.e., they operate in states with the weak enforcement of non-compete provisions). This result shows that executives who are unable to capitalize on these outside options are not experiencing a pay increase. Lastly, we document that tweeting managers are more likely to be promoted to a CEO position (but the compensation increase is incremental to the promotion). Overall, tweeting increases an executive's outside opportunities, leading to a better bargaining position of tweeting executives.

Although it is possible to find alternative explanations for some of these tests independently, it is harder to find one that can fit all of our results simultaneously. By establishing multiple conditional relationships, these different tests impose an empirical structure that reduces the likelihood that a correlated omitted variable explains our findings. For example, any omitted variable would have to be correlated in such way that it can *simultaneously* explain our results based on the level of professional mobility, the number of prior Google searches, the focused nature of the following, the debilitating effect of compensation consultants, the "busyness" of the employer, and the use of directed tweets. It would also have to account for a differential effect on public and private boards.

As with any empirical study, our approach may be affected by endogeneity. Aside from noting the multiple comparative statics and ancillary results, we address this concern in different ways. First, we note that academic research (e.g., Toubia and Stephen 2013) has shown that individuals start tweeting simply to enjoy the activity. In other words, obtaining personal benefits (such as improved career prospects) does not seem to be the primary driver behind the decision to start tweeting in the general population. Second, we find that the decision to initiate personal activity on Twitter is uncorrelated with *ex ante* indicators of positive career outcomes. For example, tweeting activity (e.g., the decision to open a Twitter account, the number of tweets posted, or the use of directed tweets and hash tags) is uncorrelated with past changes in compensation, with past levels of compensation, or with the multiple characteristics that enhance the expected benefits of tweeting. Executives who would benefit more from tweeting do not engage more in the activity. Third, personal tweets contain limited information. Reading tweets and conducting a more systematic analysis indicate that most of the personal tweets in our sample are indeed devoid of economic content. An overwhelming majority of the tweets are very informal. For example, only 2% contain formal business-related keywords (as defined in Boone, Schumann, and White 2015), and 3% mention an executive's employer. This lack of economic substance is unsurprising given that executives are subject to Security Exchange Commission (SEC) regulations and other laws that put strong constraints on what can publicly be discussed. In contrast to conference calls (e.g., Li et al. 2012) or television interviews (e.g., Kim and Meshke 2014), the average market reaction on tweeting days is not statistically different from that on non-tweeting days. Finally, some practitioners (McGregor 2017) has suggested that the use of executive's Twitter account for corporate public relations is rather infrequent. Even if executives post tweets evoking elements that might be favorable to their employers (e.g., various corporate actions, social engagement, or employee diversity), or are part of a concerted campaign with their employer, we find that these elements are not sufficiently material to affect firms' current or future economic performance and valuation. This last finding also suggests that executives do not start tweeting ahead of positive news for their employer that could affect their compensation indirectly.

We note that our framework is predicated on the notion that tweeting helps undervalued managers compensate for the limited attention from which they suffer. This in turn allows them to generate more outside offers and to improve their internal bargaining position. This framework does not generate strong priors regarding whether the managers understand the benefit of tweeting *ex ante*. Executives can start tweeting because they actively engage in self-promotion, because they enjoy the activity for idiosyncratic reasons (and thus reap the benefit unexpectedly), or even because they want to help their employer (and receive some personal benefit indirectly). Our goal is not to distinguish between these possibilities. Irrespective of their motivation, we find that the main predictions of the framework are validated by the data. However, the results discussed in the paragraph above are more consistent with the notion that executives, on average, initiate tweets for idiosyncratic reasons historically. It is certainly possible that they may start using Twitter more strategically as its benefits have become more well-known. We also do not claim that tweeting is the best or only way to raise an executive's profile. However, this medium has broad appeal, and the restriction to 140 characters reduces the likelihood that anything substantial is disclosed (our empirical results support this prior). This allows us to focus on the effect of attention rather than on information extraction that may lead to learning about executives' marginal productivity.

The remainder of this paper proceeds as follows. In Section II, we develop our hypothesis. We discuss our data and sample in Section III and explain our empirical design in Section IV. We present our baseline results in Section V. We also analyze the potential effects of endogeneity in this section. We review the results from our comparative statistical analysis in Section VI and additional analysis in Section VII. In Section VIII, we investigate alternative explanations. Section IX concludes the paper.

II. Hypothesis Development

Humans are cognitively bounded. In particular, there is a limit to the number of signals the brain can process and internalize. Hence, attention is selective and requires effort. To use economic terminology, processing information is costly and takes cognitive energy away from other tasks (e.g., Kahneman 1973). As noted by Hirshleifer and Teoh (2003) among others, cognitive effort is required to both encode environmental stimuli (e.g., corporate performance announcements) and process ideas in conscious thought (e.g., the appraisal of the value of an executive). Dukas (2004) provides a review of the neuro-biological, psychological, and evolutionary mechanisms explaining limited attention, noting (p. 197) that "the neurobiological mechanisms underlying limited attention have been widely studied" and that research suggests "limited attention is an optimal strategy that balances effective yet economical search for cryptic objects."

The effect of limited attention is studied in the finance literature, but mainly from an asset pricing perspective. The basic tenet of this line of research, at least since Merton (1987), is that the value of a security increases with investor recognition. This effect is stronger when the asset is more idiosyncratic (e.g., Lehavy and Sloan 2008). As noted by Odean (1999) and Barber and Odean (2008), investors do not buy all stocks that catch their attention; for the most part, however, they buy only stocks that do. We hypothesize that a similar mechanism applies to human capital and, more specifically, to executive value. We argue, similarly to Merton (1987) but applied to a different context, that gathering information about an asset (human capital in our case) requires cognitive resources and that this cognitive effort may be better spent following only a few items (executives, in our setting). Boards do not hire all executives who catch their attention, but they do not hire executives of whom they are unaware. Naturally, this has implications for the welfare of these executives; the less salient their profile, the lower their market value. As their notability increases, executives benefit from a growing potential demand for their talent. Consequently, previously underappreciated managers generate greater external employment options and enjoy greater market value.

We hypothesize that a presence on social media, such as on Twitter, increases executive recognition among directors and headhunters and therefore generates more options for these executives. This theoretical framework conceivably applies to social media channels other than Twitter (such as Facebook or LinkedIn). For example, Jobvite (2014) shows that 93% of recruiters review a candidate's social profile before making a hiring decision and 55% of recruiters reconsider a candidate based on her social profile (e.g., profanity, spelling/grammar, reference to alcohol, or sexually explicit posts). However, Jobvite notes that Twitter is one of the Top 3 social networks used to screen job candidates across industries.[1] A recent survey indicates that two thirds of Fortune 500 CEOs who use social media focus on one platform.[2] Among all the major networks, Twitter is the second-most popular social media platform, behind LinkedIn but ahead of Facebook, Google+, and Instagram. In contrast with Twitter, the percentage of CEOs on LinkedIn has decreased in recent years. Academic research (e.g., Toubia and Stephen 2013) has recognized the popularity of Twitter and its rapid audience growth. Twitter has also become a major component of advertising campaigns. For example, according to surveys, 74% of polled marketers indicate that brand managers use Twitter as a social media channel in their advertising campaigns.[3] Toubia and Stephen (2013) also show that posting content on Twitter is a way for users to attract new followers (and hence to presumably raise their profile).

Aside from its popularity, focusing on personal tweets by executives allows us to better isolate the effect of limited attention for several reasons. First, it is harder to convey

[1] More information available at http://www.jobvite.com/wp-content/uploads/2016/09/RecruiterNation2016.pdf.
[2] More information about the report is available at http://www.ceo.com/social-ceo-report-2014/.
[3] See http://www.exactdrive.com/news/advertising-spend-trends-on-facebook-twitter-and-youtube.

economically relevant information in the 140 characters of a tweet; one can post richer and more informative texts on Facebook and LinkedIn. Twitter allows focus on the more attention-grabbing part of social media activity (as opposed to the communication of information, for example, regarding their employers). This activity is free and does not require approval from outside parties (in contrast to appearances on television programs, publishing newspaper articles, or speaking at conventions, for example). It does not require much time, and extremely busy elected officials find the time to engage with it. A second explanation is that the reasons for initiating Twitter activity have been researched in the marketing field. For example, Toubia and Stephen (2013) find that social media users go through two phases "where intrinsic utility posting is larger than image-related utility when they have fewer followers but image-related utility becomes larger than intrinsic utility as they amass more followers." In other words, their results indicate that many individuals start tweeting because "it is fun to communicate this way with other people in the community" but may continue after finding an audience because "my contribution shows others that I am a clever consumer." Thus, an individual's decision to initiate activity on Twitter appears to be unrelated to career concerns (we provide additional support for this hypothesis below). For example, executives post such things as photos from an afternoon baseball game family pictures, or holiday season's greetings. This is less likely to be the case for LinkedIn (a business- and employment-oriented social networking service) or Facebook.

Our basic hypothesis is that an increase in notability should lower biases associated with limited attention problems and improve the bargaining position of executives. Although our motivation relies on a well-established theory, it is not a foregone empirical conclusion that it applies to our setting. It is possible that firms, especially large listed ones, dedicate such a large amount of resources to executive search and compensation setting that the attention constraint is not binding in most cases. Whether this is the case or not remains an empirical question.

Note that this reasoning does not imply (though neither does it preclude) that directors and headhunters are able to explicitly attribute the increase in recognition to Twitter. Similarly, our prediction neither implies nor precludes that executives initiate tweeting for strategic reasons (such as obtaining a promotion). In fact, academic marketing research suggests that many individuals start tweeting because they derive intrinsic utility from this activity and subsequently discover the potential benefit for their image.

III. Data and Sample

We obtained compensation data from Execucomp, financial information from Compustat, stock market data from the Center for Research in Security Prices (CRSP) database, and personal characteristics from BoardEx. To maintain the labor-intensive analysis of the tweeting activity at a manageable level, we started from a complete list of executives from Execucomp who served as a CEO at some point during the 2006–2014 period (Twitter was founded in 2006). Execucomp covers the S&P 1500 and companies that were once part of the S&P 1500 index and are still trading. Overall, 3,933 executives worked as CEOs at least once in a year during the sample period. This focus on CEOs is consistent with numerous studies in the literature (e.g., Edmans et al. 2017). Next, we manually checked the names of these managers using the search engine provided by Twitter (https://twitter.com/search-home) and obtained a list of accounts that match the managers on our list by executive names.

We then physically read tweets and other related information to determine whether each account is valid and accessible. We define "valid and accessible" using the following criteria:

(1) the Twitter account does indeed belong to the manager in question who served as a CEO at some point after opening her account, which we determine by cross-checking name, gender, company information, and profile picture; and (2) the account allows public access, and therefore its tweets are visible to outsiders.[4] We use the Twitter application program interface (API) to retrieve the full text of each tweet issued.[5] We characterize an account as active if the executive posts more than three tweets in a year over our sample period. This procedure yields a treatment sample of 101 managers with valid, accessible, and active personal Twitter accounts and for whom we can obtain the necessary data to conduct our tests.

To construct our control sample, we focus on the remaining executives who served as CEOs (at some point) since 2008 (the first personal Twitter account among the executives in our treated sample appeared in 2008). In other words, our treatment and control samples are equally successful. We ensure that we have at least two years of observations before the initiation of Twitter activity to maintain a proper treatment period for these managers. We form our control sample with executives who either do not own a Twitter account or own an inactive one.[6] Taken together, the above sampling procedure leads to 16,260 manager-years, in which 101 are treatment managers (672 manager-years) and 2,640 are control managers (15,588 manager-years).

[4] We delete managers whose Twitter accounts meet one but not both criteria, but our results are not sensitive to this design choice.
[5] More information about the Twitter API is available at https://dev.twitter.com/rest/public. This utility provides the most recent 3,200 tweets for any given Twitter account. Only four executives in our sample had more than 3,200 tweets. Our results are not affected if we exclude those four executives.
[6] Our results are not affected if we drop those managers who have a Twitter account but are consistently not active in Twitter from the control sample.

IV. Research Design

We begin our analysis by testing the prediction that being active on Twitter helps managers obtain higher compensation. Specifically, we estimate the following generalized difference-in-difference model:

$$Comp_{i,j,t} = \alpha_0 + \alpha_1 \, Twitter_{i,t} + \alpha_k \, X_{i,j,t} + \gamma_j + \sigma_n + \varepsilon_{i,j,t} \quad (1)$$

where *Comp* is the total annual compensation of a manager in a given year, including salary, bonus, other annual compensation, total value of restricted stock granted, fair value of stock options granted, long-term incentive payouts, and all other pay. As compensation data are highly skewed, we follow prior studies (e.g., Cadman, Carter, and Hillegeist 2010) and calculate *Comp* by taking the natural logarithm of the total annual compensation (in thousands of dollars). However, our main results are not affected if we use the dollar value of annual compensation (untabulated). Our variable of interest is *Twitter*, an indicator variable that takes the value of 1 if a manager has her Twitter account active in place by the end of year t and 0 otherwise.

γ_j denotes firm fixed effects. σ_n denotes industry-year fixed effects (Fama and French 48 classification). The firm fixed effects control for any time-invariant firm-level factors that affect the level of executive compensation (e.g., long-term corporate policy), and the industry-year fixed effects account for time-varying industry effects.[7] This research design essentially represents a difference-in-difference approach in which managers who have not opened their Twitter accounts in a given year serve as the control group for managers who have Twitter accounts in that year. The coefficient α_1 is our difference-in-difference estimate, which captures the average Twitter effect for the treatment group relative to the control group. Specifically,

[7] Our results are not affected if we include fixed effects based on lagged market capitalization deciles to control for the potential effect of peers of similar size (e.g., Focke, Maug, and Niessen-Ruenzi 2017).

we predict a positive coefficient on *Twitter* (α_1) if the Twitter activity increases executive compensation. As Model (1) includes firm and industry-year fixed effects, the variation is purely within firms and industries, raising the bar for identifying the impact of Twitter on executive compensation. Our results are not affected if we replace firm and industry-year fixed effects with firm-year fixed effects (untabulated).

Furthermore, we include a set of control variables (*X*). First, we control for various firm characteristics that affect the level of compensation. *Size* is the natural logarithm of total assets in place (e.g., Cadman, Carter, and Hillegeist 2010). *ROA* is income before extraordinary items scaled by total assets, as prior studies (e.g., Murphy 2000) show that accounting performance helps to determine executive pay. We also control for stock return, *Return*, to capture the effects of stock performance on compensation. *MTB* is the ratio of market value and book value of assets. Following prior studies (e.g., Core, Holthausen, and Larker 1999), we use this variable to control for growth opportunities. We expect compensation to be higher in firms that are larger, more profitable, and growing. In addition, consistent with other empirical research on compensation (e.g., Smith and Watts 1992; Core 1997), we include firm risk (*RetVolt*), measured by the standard deviation of a firm's stock return in the regression. Theoretical models (e.g., Banker and Datar 1989) provide conflicting predictions on the direction of the relationship between risk and compensation, but Core et al. (1999) empirically find a negative relation. Next, we control for the executive's position within her firm. Specifically, *CEO* is an indicator variable that takes the value of 1 if a manager currently serves as a CEO and 0 otherwise. *Tenure* is the number of years the manager has been working as a CEO. We expect compensation to be higher for CEOs and for those with a longer tenure.

Standard errors are robust and allow for clustering at the industry level to mitigate the concern that Twitter activity is potentially correlated within industry. Our inferences do not change if we cluster observations at the firm or manager level or if we remove the clustering.[8]

V. Baseline Empirical Results

Descriptive Statistics

Panel A of Table 1 reports the main summary statistics for our primary sample. Panel B reports the pair-wise correlation matrix. Consistent with our expectation, *Twitter* is significantly and positively correlated with *Comp* based on both Pearson and Spearman correlations. The univariate correlations between control variables are low, suggesting that multi-collinearity is not a severe concern in our tests. To confirm this, we examine the variance inflation factors (VIF) in our different specifications and find that they are all below conventional levels (untabulated).

To reduce the influence of outliers, control variables with continuous values are winsorized at the 1% and 99% levels. However, the untabulated results suggest that outliers are still present. This issue is common in the studies of executive compensation (e.g., Guthrie, Sokolowsky, and Wan 2012). To mitigate this problem, we exclude observations with a DFBETA diagnostic value greater than 0.05 (e.g., Belsely, Kuh, Welsch 2005). This method addresses outliers in both the dependent variable space (i.e., vertical outliers) and the independent variable one (i.e., bad leverage points). It has been used in prior literature (e.g., Sedor 2002; Dee, Lulseged, and Nowlin 2005; Munk, Bonke, and Hussain 2016). Our results are more significant if we do not exclude any outliers. Our conclusions are also unaffected if

[8] The falsification test in Section 3 further explains why the choice of clustering does not affect our inferences (e.g., Bertrand et al. 2004; Rosenbaum 2002, 2009).

we drop observations of when executive compensation (TDC1) for the year (1) is extremely low (e.g., does not exceed 1, 100, or 1,000 dollars), or (2) is greater than two standard deviations of the sample mean (Song and Wan 2017).

Our final sample includes 2,732 managers, composed of 97 treatment managers (578 manager-years) and 2,635 control managers (15,560 manager-years). The untabulated results show that the number of managers with Twitter accounts increased from 0 in 2006 (2 executives in 2008) to 4% of our sample at the end of our sampling period (2014). We also use econometric techniques to mitigate the concern that an unbalanced panel may affect our results (we describe them in greater depth in Section V).

Baseline Results

We present the main results in Panel A of Table 2. In column (1), we regress *Comp* on *Twitter* with firm and industry-year fixed effects. In column (2), we further include firm and individual characteristics that could be correlated with pay. The estimated coefficient on *Twitter* is significant at the 1% level and fairly stable across the two columns. In column (3), we include *Twitter_Firm*, an indicator variable that takes the value of 1 if the firm (as opposed to the executive) has a valid and active Twitter account in year t and 0 otherwise. The (untabulated) correlation between *Twitter* and *Twitter_Firm* is weak (0.09). *Twitter_Firm* is insignificant, and the point estimate of the coefficient associated with *Twitter* is left essentially unaffected when we include this variable in the regression. In addition, our conclusions remain unaffected when we replace firm fixed effects with executive effects (columns 4 and 5). In terms of economic significance, initiating activity on Twitter is associated with an increase in compensation of approximately 10% of its mean value.[9] [10] This increase is approximately translated to 14% of the economic effect associated with being named CEO.

Our results (untabulated) are not affected when we focus only on the log of salary or measure the option value using the realized total compensation instead of the fair value of stock options granted.[11] The results also hold when we lag the control variables by one period. In addition, we conduct a set of additional analyses to rule out the possibility that the link between compensation and Twitter arises because of individual-level omitted variables. The results are not affected after controlling for an extensive list of specific observable individual-level variables that are related to executive compensation. For example, including the executive's personal characteristics, such as education, age, gender, and chairperson position, the size of the executive's personal network, and the number of news articles about the executive in six major business publications, does not change the conclusions.[12] The results continue to hold when we control for firm-level time-varying measures of corporate transparency, such as analyst forecast dispersion, analyst forecast errors, analyst following, the bid-ask spread, and abnormal accruals (Armstrong, Balakrishnan, and Cohen 2012). Finally, the results also hold when we control for state-level variables, such as the unemployment rate, level of or change in median household income, and the percentage of minorities in the population.

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[9] We calculate the economic effect as based on the exponential value of 0.095 (the coefficient on *Twitter* in Column 4 of Table 2 Panel A) minus one.

[10] Studies conducted by practitioners (e.g., https://www.cnbc.com/2017/04/13/the-surprising-reason-why-ceos-should-be-social-media-savvy.html) have found a correlation between CEO stable attributes and having a Twitter account. Managerial fixed effects control for these potential effects. As discussed below, our results are stronger when we focus on the managers who were not CEOs when they start tweeting.

[11] We use the TDC1 variable from *Execucomp* in our test. Using TDC2 in this robustness test does not affect our conclusions.

[12] Education is measured by the number of degrees at the undergraduate level and above from BoardEx. For example, an individual with a bachelor's degree and a master's degree would be coded as two. BoardEx provides the size of the personal social network. The network is measured by the number of overlapping organizations and activities of a manager with others through employment, education, and other activities. For example, an individual who has worked with five executives in the same company, studied with 10 executives in the same college, and been a member of a golf club with two executives would be coded as 17. To count the number of a manager's news articles, we searched Factiva for articles referring to the managers in our sample in *The New York Times, BusinessWeek, Financial Times, The Wall Street Journal, The Economist, Fortune,* and *Forbes*.

As discussed previously, there may be concern that our results are affected by the imbalance in the sample between tweeting and non-tweeting executives. We consider different techniques to address this issue. We start with an entropy balancing (EB) approach. EB is a reweighting procedure that directly incorporates covariate balance into the weight function. Specifically, the EB approach assigns a scalar weight to each sample unit such that the moments of the control variables for the reweighted control group equal the moments for the treatment group, creating a balanced sample for the subsequent estimation of the treatment effect (Hainmueller 2012; Hainmueller and Xu 2013). The EB approach reduces the effect of some potential misspecification (e.g., observable omitted variable) in the estimation of treatment effects (Abadie and Imbens 2007; Ho et al. 2007). We first use the EB method to balance the first three moments of the control variables: the mean, variance, and skewness. The results reported in Appendix A show that all three moments of the control variables for tweeting and non-tweeting managers become approximately equal with only a marginal difference after the EB procedure is implemented. This suggests that the level of homogeneity between treatment and control samples is high. Next, we follow prior studies (e.g., Robins, Rotnitzky, and Zhao 1995; Hirano and Imbens 2001) and re-estimate Model (1). Columns (5) and (6) in Panel A shows that *Twitter* remains significant and the magnitude of the coefficient is not affected.

We perform various robustness checks to further ensure that the imbalanced panel is not problematic. First, we create a matched sample using a nearest-neighbor propensity score matching technique. To this end, we follow Rosenbaum and Rubin (1983) and estimate a discrete-time hazard model that examines a manager's choice to initiate a Twitter account. We include the control variables in Model (1) in the model and use the predicted probabilities from the model as the propensity score. We match each tweeting manager to the control manager with the closest propensity score with replacement (using 0.05 as the caliper distance) to form a sample of treated and control managers within the same calendar year. Next, we repeat our analysis using an inverse probability weighting procedure (e.g., Hirano, Imbens, and Ridder 2003; Busso, DiNardo, and McCrary 2014). We follow previous studies (Rosenbaum and Rubin 1983; Imbens and Rubin 2014) and use the estimated propensity score to weight the outcome variable. Finally, we follow Hainmueller (2012) and combine a propensity score technique and the EB method to achieve greater overlap between the treatment and control groups. We repeat our EB approach using the sample after removing extreme observations with no common support (propensity scores are not within the 1 and 99 percentiles). The untabulated results indicate that our results from the preceding robustness checks are not affected.

Endogeneity

A perennial issue with much of the empirical literature in applied economics is endogeneity. We address this issue below with multiple empirical approaches. However, before discussing the details of these approaches, we examine whether the data are consistent with endogeneity in our setting. We stress that this part of the analysis is not central to what we test.

First, we note that we focus on personal rather than company-initiated tweets. As discussed above, prior studies (e.g., Blankespoor, Miller, and White 2014; Lee, Hutton, and Shu 2015; Al Guindy 2016; Jung, Naughton, Tahoun, and Wang 2017) show that company-initiated tweets mostly contain corporate disclosures that attenuate market reactions to negative news, increase transparency, reduce the cost of capital, and improve stock liquidity. As discussed above, firm and executive tweeting activities are very weakly correlated. Research (e.g., Bartov, Faurel, and Mohanram 2017) has also shown that analysis of market sentiment using an extremely large number of tweets posted by individuals unaffiliated with the company (the "wisdom of crowds") can predict a firm's future. Our focus is on personal tweets issued by executives who are subject to SEC regulations and other laws that put strong constraints on what they can publicly discuss. However, the marketing research we discuss above suggests that the primary reason for initiating personal tweeting activity is its intrinsic value (i.e., "it is fun to communicate this way with other people in the community"). This finding suggests that the decision is largely exogenous with respect to the increase in compensation that we study.

We conduct multiple additional tests to buttress this claim. First, we read a large cross-section of personal tweets. Most are conversational, very casual, and devoid of economic meaning. For example, Karl McDonnell (an executive at Strayer Education, Inc) indicated the following in his first tweet: "Just signed up for Twitter....looking forward to writing about all sorts of useless things..." Conversely, we did not identify any highly controversial materials.[13] We provide a selection of examples in Appendix B. Similarly, a majority of our tweeting managers do not use a formal profile picture but mention their personal hobbies on their Twitter page. Our results are not affected if we exclude managers who use a formal profile picture or do not mention their hobbies (untabulated).

Next, the untabulated results indicate that the average market reaction (measured by the trading volume and absolute value of return) on tweeting days is not statistically different from the reaction on non-tweeting days.[14] This lack of market reaction is also present in sub-samples. For example, we observe no difference if we focus on tweets that contain a business keyword (Boone, Schumann, and White 2015), mention the employer, mention a CNBC interview, have an embed hyperlink to another document (e.g., video, webpage, and picture), are directed at a large account, contain a hashtag, or that are retweeted. Next, even if the average reaction to tweets is zero, we expect to observe executives for whom the tweets appear correlated with

[13] Practitioners seem to concur on this point. For example, a Washington Post article by Jena McGregor published on June 6, 2017 cite a consultant as saying "…we don't really see a lot of big gaffes out there by Fortune 500 CEOs on social media."
[14] Chen, Hwang, and Liu (2016) find a small (-0.07%) negative reaction in the three days after a CEO or a CFO posts a tweet with a high fraction of negatively connoted words. This initial reaction is followed by a subsequent reversal in the next three days.

market activity (if only by chance). However, we find that the beneficial effect of tweeting on executive compensation is *not* significantly different for managers with high and low tweet price impacts (the *p*-value equals 0.76).[15] This result further supports the idea that the career-related benefits of tweeting are not related to the communication of value-relevant information.

Next, we examine whether executives are more likely to tweet when they expect to derive more benefit from their activity. First, we create a first indicator variable that takes the value of 1 if an executive is not a CEO and the current CEO is close to retirement (i.e., at least 60 years old) and zero otherwise. We create a second indicator that takes the value of one if an executive is not a CEO and the current CEO changed in the year *t*-1, 0 otherwise. We then regress *Twitter* on both variables and on the control variables present in Model (1). The untabulated results indicate that the coefficient on both variables is insignificant. Second, we regress *Twitter* on an indicator variable indicating that the CEO has changed in a window that starts two years earlier and finishes two years later. This indicator variable is also insignificant. Third, we create a score based on the different partitioning variables (used in comparative statics) that are shown to be associated additional benefits for managers who tweet. We form a variable *ExpBenef* based on five specific characteristics.[16] We then regress *Twitter* on *ExpBenef*, controlling for our standard vector of variables present in Model (1). The untabulated results indicate that the coefficient on *ExpBenef* is insignificant, showing that managers who are expected to benefit the most from tweeting do not tweet more. This result is consistent with some practitioner studies (e.g., McGregor 2017) suggesting that CEOs do not tweet more because "they don't understand its return on investment." We also examine whether the level

[15] We measure the tweet impact using either the trading volume or the absolute value of the return on the tweeting dates. We use the median as the breakpoint.

[16] Specifically, we consider managers' pre-tweeting pay level, tenure, reputation as measured by the frequency of being searched on Google, positions they have held, their potential job mobility as measured by the stringency of non-compete provisions, and the use of compensation consulting. Using the sample of managers who initiated tweeting, we regress the changes in compensation after tweeting on the above five variables. We then use the parameters from the regression to estimate the expected benefit of tweeting for all managers.

of historical compensation drives the initiation of Twitter activity. Specifically, we regress *Twitter* on averaged lagged changes (from years t-3 to t-1) in *Comp* and on the control variables present in Model (1). Alternatively, we use the lagged level of compensation (from t-3 to t-1). These lagged values are insignificant, indicating that the tweeting activity is not affected by past trends in executive pay. We obtain similar results in the above tests if we use the number of tweets, the number of directed tweets, and the frequency of hashtags used as the dependent variable instead of *Twitter*.

Next, there may be concern that the activity on Twitter is correlated with a broader public relations campaign orchestrated for the promotion of executives. We note that if true, this would not invalidate our main hypothesis, which is that the executive market suffers from biases induced by limited attention. However, we find only 3% of the personal tweets use one of the keywords regarding other media exposures (e.g., “interview,” “press,” “TV,” “convention”) and that less than 3% mention the executive’s employer. Our results hold if we exclude these observations.

Finally, it is possible that the tweets enhance firm value, for example by improving the company image, which may indirectly increase executive compensation (e.g., Malhotra and Malhotra 2016). In this context, it is possible that specialized consultants write tweets on behalf of executives (Murphy and Sandino 2010; Rajgopal, Taylor, and Venkatachalam 2012). We note that this possibility would still be consistent with our main predictions. In addition, it is possible that executives start tweeting when they expect their employer to release positive news that may have an indirect increase on the executives’ compensation. To explore these possibilities, we regress various proxies of firm value (e.g., Tobin’s Q ratio, stock return, ROA, sales growth, and assets turnover in the following two years) on *Twitter* and the control variables in Model (1). None of the proxies has a significant relationship with personal tweets.[17] This suggests that personal tweeting activity does not have a significant positive impact on firm value and firm performance (or is not timed ahead of positive developments). These results also show that any improvement in executive skills (that might be correlated with the Twitter activity) have no effect on firm performance.

Taken together, these findings are consistent with the notion that initiating social activity on Twitter is fairly exogenous in our context. However, it is certainly possible that this finding was true historically but that executives and their employers have become more strategic as the benefits of tweeting have become better known.

Time Series Dynamic and Placebo Tests

The results from these numerous tests notwithstanding, we use additional approaches to address potential endogeneity. First, the baseline specification above provides little information on the dynamics of executive compensation. To explore this issue, we decompose *Twitter* into separate periods for each tweeting manager and create two new indicator variables (*Prej* and *Postj*, respectively). More specifically, we re-estimate our models from Model (1) by replacing *Twitter* with those decomposed variables. *Prej* (*Postj*) is an indicator variable that takes the value of 1 for exactly j years before (after) a manager opens her Twitter account and 0 otherwise. Similarly, *Post2+* is an indicator variable that takes the value of 1 two years or more after a manager opens her Twitter account and 0 otherwise. The results in Panel B of Table 2 (column 1) show that the increase in *Comp* does not occur before Twitter activity is

[17] The exception is sales growth, which is *negatively* associated with a tweeting activity in some specifications. This is in contrast to some survey results (based on "several hundred employees of diverse companies") suggesting that a majority of these individuals believe that CEO participation on social media channels help enhance brand image (http://www.brandfog.com/CEOSocialMediaSurvey/BRANDfog_2012_CEO_Survey.pdf).

initiated. These results suggest that the parallel trend assumption behind our difference-in-difference analysis is not problematic in our setting. Importantly, the coefficient on *Post0* and *Post1* are positive and significant, suggesting that the increase in *Comp* started after the executives initiated tweets. The effects continue to hold in the two years after a manager's initiation of Twitter activity, reflected by the positive and significant coefficient on *Post2+*. This result suggests that the effect of Twitter is not short-lived.

Second, our panel may suffer from the "Big N, Small T" problem that leads to inconsistent estimates (Arellano and Bond 1991). To ensure that fixed or slow-moving managerial characteristics are not driving the results, we estimate Model (1) without firm fixed effects. Instead, we include lagged compensation to account for other unobservable firm and managerial characteristics (Core et al. 1999). Since including lagged dependent variables in a dynamic panel can induce estimation biases, we follow the system generalized method of moments (GMM) procedure of Blundell and Bond (1998). The untabulated results indicate that this specification passes the Sargan and Arellano-Bond tests for zero autocorrelation. Column (2) in Panel C shows that the results continue to hold. This suggests that the results are likely not driven by time-invariant and slow-moving omitted variables (e.g., executive ability, psychological characteristics) or by a reverse causality issue.

Third, we follow Bertrand, Duflo, and Mullainathan (2004) and randomly select a set of *manager x year* cells, defining them as "pseudo twitter events." We then estimate the baseline regression model using the pseudo Twitter events instead of real Twitter events and store the estimated coefficients from the pseudo regressions. The placebo tweeting distribution provides a way to conduct statistical inference with less restrictive assumptions than those required for standard methods. Based on 2,000 regressions with simulated data, we find that both the mean and media values of the placebo Twitter effect are zero. The observed estimate of the Twitter effect (as reported in Panel A of Table 2) falls in the extreme tail of the distribution of placebo effects. This suggests that our estimate of *Twitter* is extremely unlikely to have arisen by chance and that an omitted variable would have to be highly correlated with our treatment variable to explain our results.

Instrumental Variables (IVs)

We also consider different IV specifications to further rule out any remaining endogeneity concerns. Our instrument, *Twitter_Popularity,* is the percentage of managers in our entire sample (of 2,732 executives) who use Twitter accounts in a given US state at the beginning of a calendar year. We exclude the treated manager under consideration from the calculation of *Twitter_Popularity* (e.g., if five executives out of 10 present in the state tweet, the value of *Twitter_Popularity* is four divided by nine if the executive tweets and five divided by nine if she does not).

Studies on social contagion show that geographic proximity is one of the key factors that predicts technology adoption because social learning about technology promotes its diffusion (e.g., Conley and Udry 2010). Consistent with this view, researchers find that the geographic distribution of individuals' propensities to adopt social media and the preferences of peers who share similar tastes and geographic locations are crucial features in describing the adoption of Twitter (e.g., Takhteyev, Gruzd, and Wellman 2012; Toole, Cha, Gonzalez 2012). In addition, we do not see a clear reason for why the regional propensity among executives to adopt Twitter should affect managerial compensation, especially after controlling for firm and industry-year fixed effects. In other words, we expect the instrument to satisfy the exclusion criterion.

The untabulated statistics indicate that a higher proportion of users can be found in states such as South Carolina, West Virginia, and Montana, (with 14–26% of executives tweeting at some point). Some states do not have executives with an active Twitter account in our sample period (e.g., Alaska, Mississippi, and New Mexico). Large states, even those with a strong technology industry (e.g., California, Illinois, and New York) are in the middle of the distribution (with 3–5% of executives tweeting at some point). The average number of managers excluding the treated manager under consideration (i.e., the denominator of *Twitter_Popularity*) is about 56.

To obtain a statistical assessment of the quality of our instrument, we follow Lewbel (2012). This approach allows the identification of structural parameters with endogenous regressors, even in the absence of external instruments (e.g., see Larcker 2003 for a positive discussion of this approach). Identification is achieved in this context by obtaining regressors that are uncorrelated with the product of heteroskedastic errors. Lewbel (2012) shows that this approach may be applied to supplement external instruments to improve the efficiency of the IV estimator. It allows us to examine the ancillary statistics associated with an over-identified system. We report the results from the Lewbel (2012) procedure in column (1) in Panel C of Table 3.

Second, Wooldridge (2010) suggests that a three-step estimation is efficient when the variable of interest is binary. We follow his approach and first estimate a probit model in which *Twitter* is the dependent variable. We control for the variables in Model (1) and include our instrument, *Twitter_Popularity*. We obtain the fitted value from the probit model. We then use it as an instrument to obtain the IV estimators in the next two stages of regressions. In column (2), we use the Wooldridge three-stage approach with the Lewbel (2012) estimation procedure. Specifically, we use the probit method to obtain the fitted values, which are used as an external instrument in the Lewbel (2012) procedure.

Both approaches yield similar conclusions. The results are consistent with *Twitter_Popularity* being a relevant instrument. The results from the Lewbel procedure indicate that the Hansen J statistics are approximately 0.8, far above the 10% cutoff point for significance (column 1). This supports the validity of our instrument. In the first approach (column 1), the instrument (*Twitter_Popularity*) in the first stage regression is positive and significant (the untabulated *t*-statistic is 4.02). In the three-step approach (column 2), *Twitter_Popularity* is significantly positive in the first step (the untabulated *z*-statistic is 11.82). The fitted value is also significant in the second step (the untabulated *z*-statistic is 2.94). In both approaches, the Cragg-Donald F-statistic is approximately 900 (916 in one case, 899 in the other), well above the critical values of the Stock-Yogo weak ID test. This suggests the estimation does not suffer from weak instruments. Last and importantly, *Twitter* is significantly positive in both specifications, with *z*-statistics equal to 2.56, and 2.26, respectively. Our results also hold if we control for state-level variables such as the unemployment rate, level of or change in median household income, or percentage of minorities in the population. Thus, our findings are robust to using different IV specifications.

Twitter Audience

Next, we consider the effect of the Twitter audience, rather than the mere act of initiating a tweeting activity. To this end, we decompose *Twitter* into two sets of variables: *High_Twitter* and *Low_Twitter*. *High_Twitter1/2* (*Low_Twitter1/2*) are a series of three sets of indicator variables measuring whether a manager has a large (small) number of followers on Twitter (*High_Twitter1*, *Low_Twitter1*), or is followed by focused (unfocused) accounts (*High_Twitter2*, *Low_Twitter2*). In each specification, the default case in this specification is a complete lack of Twitter activity.

First, we define a manager as having a large (small) number of followers if the number of followers is above (below) the value of the top tercile for all of the tweeting managers in our sample. Next, we define a manager as having a focused following if the median number of accounts followed by the executive's audience (the secondary following) is below (above) the median value of secondary following for all of the tweeting managers in our sample. For example, if an account is followed by three people who are themselves following three, six, and nine accounts, the secondary following is six. As the median secondary following in our sample is 479, this executive would be coded as having a focused following. When a manager benefits from a more focused following, we expect her to garner greater attention. We then re-estimate Model (1) by replacing *Twitter* with *High_Twitter* and *Low_Twitter*. We use the same set of independent variables as in column (2) in Panel A. Consistent with the notion that the benefits from Twitter are stronger for more visible accounts, the coefficients on *High_Twitter* are significantly greater than those on *Low_Twitter* in both cases (Panel D of Table 2). In other words, the Twitter audience matters for executive compensation. This finding reduces the likelihood that an omitted variable, such as a change in managerial mood or in training, explains our results.

VI. Comparative Statics

Next, we examine different comparative statics tests that are suggested by our limited attention framework. We do so to further examine whether limited attention explains the benefits of tweeting for managerial compensation and to further rule out the possibility that an unspecified correlated omitted variable explains our findings.

Attention Deficit

Our limited attention framework suggests that managers who tweet when more people are paying attention should derive a greater benefit from their social media activity. Consistent with this claim, the benefit of tweeting is greater if managers are followed by a larger audience. However, we expect the impact of Twitter to be moderated by the pre-existing level of attention. Specifically, we expect Twitter to have a more limited effect for managers suffering from a smaller attention deficit (i.e., those who are already well known may face a declining marginal return on their online activity). To test these predictions, we consider three proxies for a pre-existing level of attention deficit (*Attention_Deficit*). Specifically, we create four indicator variables based on (1) whether the executive is *not* a CEO, (2) whether the frequency of Google searches using the executive name as a keyword is smaller than the upper tercile of the frequency, and (3) whether the length of tenure at the firm is smaller than the upper tercile of the length. All three variables are based on the status in the year before the initiation of the activity on Twitter.[18] We then interact each indicator variable with *Twitter*. The results presented in Panel A of Table 3 are consistent with expectations. In particular, they indicate that the benefit of Twitter is concentrated among executives with a low pre-existing level of notoriety.

Tweeting for Attention

Next, we examine whether the benefit of Twitter is greater when executives use techniques that maximize its impact. To this end, we consider three proxies. First, we expect a manager to obtain greater attention when she tweets more frequently. Second, as the usage of

[18] Using the CEO's status at the time of the tweets does not affect our results.

the hashtag (i.e., "#") in tweets can increase impact, we expect that a greater use of hashtags provides greater recognition. Third, we expect a manager who issues more directed tweets (i.e., tweets using the @ function to link with high-profile accounts) to attract more attention and thus expect her tweets to have a greater impact on her notoriety and career.

To empirically test these conjectures, we create two indicator variables. *High_ Attention_Twitter* equals 1 if a manager with Twitter activity (*Twitter*=1) uses techniques to increase her profile and 0 otherwise. If the executive is engaged in tweeting but does not often use one of the attention-enhancing techniques, *Low_Attention_Twitter* is coded as 1 and 0 otherwise. We operationalize this approach by examining whether each of these three metrics is above the value of the top tercile: (1) the number of tweets posted in a year, (2) the average number of hashtags used in a tweet in a year, and (3) the percentage of directed tweets made in a year. A directed tweet is one that uses the @ function to establish a link with a high-profile account (e.g., an influential user such as Bill Gates, or another S&P 1500 company's Twitter account). An example is "Thanks, @Delta for offering @SquawkStreet in flight. Makes trip go faster…" (tweeted by Karl McDonnell, CEO of Strayer Education on February 26, 2014). "Delta" has 1,317,490 followers on Twitter and "SquawkStreet" has 126,216 followers. We define high-profile accounts as those having more followers than the median value of all the accounts that are mentioned in the managers' tweets.

We next re-estimate Model (1) by replacing *Twitter* with *High_Attention_Twitter* and *Low_Attention_Twitter*. Our attention framework suggests that the coefficient on *High_Attention_Twitter* should be greater than that on *Low_Attention_Twitter*. The results in Table 5 indicate that the benefit of tweeting activity is significantly higher for managers who use attention-enhancing techniques.

VII. Outside Options and Career Development

Prior Compensation Level

We argue in the introduction that a labor market with limited attention may undervalue some managers. These individuals should derive more benefit if they can increase their notoriety. To investigate this conjecture, we divide our sample into terciles based on the residual value from Model (1) but excluding *Twitter* from the list of independent variables. The lower (higher) tercile includes observations for which under- (over) compensation is more probable. The results in Panel C of Table 3 are consistent with this view. We find that the benefits of tweeting on compensation accrue to the lowest tercile group. The coefficient on *Twitter* is positive and significant (the *t*-statistic equals 6.13). Being active on Twitter increases *Comp* by approximately 5% of its mean for underpaid executives. By contrast, we find no significant effect on the compensation of managers in the other two terciles (i.e., cases in which managers receive their expected level of compensation or higher). We even find that *Twitter* is negative and significant (the *t*-statistic equals -1.85) when we consider the highest decile (untabulated). These results show that tweeting is not a panacea for executive compensation and can explain why not all executives tweet.

Systematic Process and Compensation Consulting

We expect the effect of increased notoriety attention deficit to be more significant when the compensation design is less systematic. For example, we expect that low compensation is more likely to be due to the mispricing of human capital when the employer does not employ a consultant to set the compensation. Thus, the benefits of tweeting should be stronger in this case. To test this prediction, we create an indicator variable, *NoConsult*, equal to 1 if the current employer hires a consultant to advise on the appropriate compensation, and zero otherwise. This variable is also based on the status in the year before initiating the activity on Twitter. We then interact this indicator variable with *Twitter*. The results presented in Panel D of Table 3 are consistent with expectations. In addition, the untabulated results indicate that if the firm does employ a consultant, the "busyness" of the board increases the benefit of tweeting (Hauser 2018).[19]

Job Mobility

We expect that if firms intend to retain managers who are active on social media because they appear more desirable, our results should be concentrated on those who can easily move to another firm. Managers with low job mobility would not garner as much interest, irrespective of their social media activity. We investigate this possibility by examining the effect of non-compete agreements. Gaimase (2011) shows that managers working in states that strongly enforce non-compete provisions are less likely to find jobs outside their current employers. Conversely, we expect managers who are subject to fewer non-compete restrictions to have higher labor market mobility and hence benefit more from Twitter activity.

We classify managers as having fewer non-compete restrictions if they are located in states where the enforcement index of non-compete covenants in Ertimur et al. (2017) is below 5 (9 being the strictest enforcement). We then re-estimate Model (1) by including an interaction term, *High_Mobility* × *Twitter*, and the standalone variable, *High_Mobility*, in each cross-sectional test. We use the same set of control variables as those presented in Table 2. The results reported in Panel B of Table 4 are consistent with the predictions. The coefficient associated

[19] We measure "busyness" by the average number of seats (private and public) held by the board members of a firm.

with the interaction between being active on Twitter and having greater mobility is positive and statistically significant (the *t*-statistics are equal to 2.25, respectively). On the other hand, we find the coefficient on Twitter *per se* is not significant, suggesting no discernable effect for managers with lower mobility. Again, the results also explain why not all executives tweet.

Other Career Outcomes

Next, we consider two other aspects of executive value: the number of directorship positions and promotions. First, we obtain the number of external board seats a manager holds from BoardEx. Serving on an outside board is an indicator of an observable executive's career opportunities outside her current employer. We consider public and private companies separately because the search for directors of public companies should be more systematic and thus less prone to attention biases. We expect the effect of attention deficit to be more significant when searches are more ad hoc and thus that the benefits of tweeting should be stronger in a sample of private firms. Second, we use *CEO* as the dependent variable.

The results reported in Table 4 support our expectations. *Twitter* is significant when we focus on the number of seats in private companies but not when we consider public companies. The difference between the two samples is significant at the 1% level (untabulated). Once a manager becomes active on Twitter, the number of external boards of private companies she serves on increases. Moreover, the results in Column 3 indicate that tweeting activity increases the likelihood of being promoted to be a CEO (the *t*-statistic equals 3.39).

VIII. Alternative Frameworks

Effective Communication and Information Sharing

The first alternative explanation for our limited attention framework is the notion that tweeting increases managers' employer visibility and that tweeting managers are rewarded for doing so. Our tests rule out this explanation. First, the correlation between *Twitter* and *Twitter_Firm* is low (0.09). Our results hold when we control for firm fixed effects and for the tweeting activity of the firm (Panel A of Table 2). Second, the untabulated results indicate no significant association between managerial tweeting activity and the frequency of Google searches for a company. Third, our results are unaffected regardless of whether we control for a firm's Google search volume or media coverage. Correlations between Twitter and these different measures of firm visibility are also very low (less than 0.1, untabulated). Fourth, personal tweets rarely mention the employer (3%, untabulated). Removing these rare cases does not affect our results. Fifth, it is not clear why executives would gain seats on private but not public boards in this context (Table 4). It is also unclear why under-searched executives would benefit more from tweeting, even though the potential impact on the firm should be lower (Table 3, Panel A, Column 2).

A related alternative explanation is that tweets convey information about the firm and that executives are rewarded for their efforts to increase transparency or the disclosure quality of their firms. Different results suggest that this does not explain our findings. First, we consider many types of executives, including those *not* involved in financial reporting (such as COOs). The results in Panel A of Table 3 indicate that the effect of tweeting is stronger for executives who are not CEOs. In addition, our baseline results continue to hold after we exclude managers who hold a CFO title (untabulated). Second, as previously discussed, most tweets lack economic substance. The market reaction on tweeting days is not statistically different from non-tweeting days. Kim and Meshke (2014), on the other hand, find significant market reactions when CEOs appear on CNBC, events that contain a great deal of firm-related information. Moreover, our results hold when we control for time-varying measures of corporate transparency, such as analyst forecast dispersion, analyst forecast errors, analyst following, bid-ask spread, and abnormal accruals (untabulated). They also hold when we control for CEO appearance on news articles and on CNBC (untabulated). Using Twitter and giving interviews on CNBC are statistically uncorrelated. Nevertheless, as discussed before, our results are not affected after deleting manager-years in which the tweets mention their employers. Finally, the majority of the tweeting managers in our sample do not have an active presence on other social media (e.g., Facebook and LinkedIn).[20] Our results are not affected if we exclude managers who have an active presence both on Twitter and Facebook or LinkedIn. In sum, our additional analysis suggests that the findings of tweeting are robust to controlling for other channels that could also potentially increase attention.

Bayesian Learning and Managerial Ability

Another alternative possibility is that employers learned about the executive marginal productivity (or a skill that was previously undetected when the executive started tweeting). This explanation would be based on extracting information about the executive managerial productivity from the tweets, even though most tweets have little content. Different results are also inconsistent with this view. For example, Bayesian learning should exist along an executive's career rather than suddenly materializing after the executive starts tweeting. In contrast, the time series test (Table 2, Panel B, Column 1) suggests that this learning, if any,

[20] We follow a procedure identical to the one used for collecting data on managerial Twitter activity to examine whether a manager maintains an active account in LinkedIn or Facebook during our sample period.

does not happen before tweeting starts, but is very rapid once the executive initiates this activity. In addition, Bayesian learning is inconsistent with the fact that employers do not learn more from tweets that are more informative or are more employer-focused (the untabulated results discussed in Section V). Bayesian learning also does not provide a good justification for the facts that employers learn more when the secondary following of the executive is more focused (Table 2, Panel D, Column 2) or that outside private boards learn more from tweeting than outside public boards (Table 4, Columns 2 and 3). Finally, prior research (e.g., Graham, Li, and Qiu 2012) suggests that managerial skill is primarily a fixed effect. Our results (including the comparative statics) are robust to including these fixed effects. In light of these findings, this alternative explanation strikes us as implausible.

Nevertheless, we investigate this possibility further using the findings of Milbourn (2003). This study argues that learning and beliefs formation by Bayesian market participants about a manager's ability that is not directly observable translates into a positive relationship between stock-based pay-performance sensitivity (PPS) and managerial reputation. In contrast to Milbourn's (2013) findings, we find the interaction terms between *Twitter* and either *ROA* or *Return* are statistically insignificant, but the main effect of *Twitter* is unaffected (untabulated). The untabulated results also show that we continue to find an insignificant association between PPS and Twitter activity when we use change in compensation as the dependent variable. This shows that the PPS is unaffected by the tweeting activity and is inconsistent with a Bayesian learning of managerial ability. Finally, our results are unaffected when we control for CEO tenure, media coverage, and firm performance, the proxies for managerial reputation, or the perception of managerial ability used in Milbourn (2003) (untabulated).

Governance

Under the limited attention framework, we expect the market value of an executive to increase when there is greater public awareness of her existence, and such benefits should be more pronounced for underappreciated and mobile managers. However, Malmendier and Tate (2009) show that award-winning managers increase their entrenchment, extract more compensation, spend more time outside the firms, and underperform compared with their prior performance and peers. Such *ex post* value destruction, however, is mitigated if firms benefit from strong shareholder rights that facilitate the monitoring of these superstar managers.

Our results are unlikely to be explained by rent extraction. First, the untabulated results fail to show a negative impact of Twitter on firm performance using various measures (e.g., ROA, sales growth, stock return, and assets turnover). Second, the benefits of Twitter activity do not decrease with the strength of corporate governance as proxied by institutional ownership (untabulated, Guo and Masulis 2015) or the E Index (Bebchuk, Cohen, and Farrell 2009). Finally, the untabulated results also indicate that Twitter use is uncorrelated with institutional ownership and is extremely weakly correlated with the E Index (-0.01).

Mood and Expected Good News

Another possibility is that tweeting captures a positive change in executive mood ahead of receiving good personal news. Again, different results suggest this possibility does not tie in with our findings. For example, it is not clear why tweeting would be associated with appointments on private boards but not on public ones, why tweeting would correlate more with increases in compensation only when executives are working in states with weak enforcements of non-compete agreements, when they are under-searched in Google, when their followers are more focused, or when the executives are more effective in their tweeting. In addition, tweeting is uncorrelated with firm performance. If expected good news was the explanation, it is unclear why executives would not tweet more when their firms are doing well.

IX. Conclusion

We rely on the well-established theory of limited attention to investigate the effect of tweeting activity on managerial welfare. Limited attention refers to the idea that people have maximal cognitive capacity to absorb information and a limit on what they can pay attention to. Signals that are more noticeable should receive more weight in decision-making. Given that executive value is difficult to ascertain, we expect these biases to play a significant role in setting the managerial market value. Thus, we hypothesize that this value should increase when there is greater public awareness of an executive's existence, particularly if she is otherwise underappreciated and compensation is not set systematically. We explore these predictions using a specific way to draw attention to an executive: tweeting.

The results are largely consistent with our hypothesis. Initiating Twitter activity increases executive compensation. This finding is robust to a battery of econometric checks. A Monte Carlo simulation indicates that an omitted variable would have to be extremely correlated with our treatment variable to explain our results. The effect starts in the year of initial tweeting and increases afterward. The data display a parallel trend in the year prior to tweeting. The benefits are stronger when managers enjoy a larger, more focused, and more active audience. Our comparative statics also show that the effect of Twitter is stronger for executives who suffer from a pre-existing deficit of attention and who use attention-grabbing

Twitter techniques. Importantly, more informative tweets do not produce a greater benefit than uninformative tweets.

Our results support that tweeting increases an executive's outside opportunities, leading to a better bargaining position of tweeting executives. For example, we find the effect of Twitter is concentrated for executives who are underpaid, who are more able to realize outside opportunities, and who work for companies that are less systematic in their compensation approach (e.g., private boards, lack of compensation consultants). In addition to increased compensation, these managers are also able to secure more seats on boards and more likely to be promoted. Again, the positive effect on the probability of obtaining additional board seats is concentrated in private companies. Our findings also suggest that not all executives have incentives to tweet. Finally, different tests (discussed in Section VIII) rule out alternative explanations, such as Bayesian learning about managerial ability.

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Table 1 Descriptive Statistics and Correlations

Panel A. Descriptive Statistics

	N	Mean	Std. Dev.	Median
Twitter	16,260	0.015	0.124	0.000
Comp	16,260	7.982	1.180	8.058
Size	16,260	7.712	1.687	7.655
ROA	16,260	0.037	0.103	0.047
MTB	16,260	1.803	1.030	1.472
Return	16,260	0.165	0.467	0.125
RetVolt	16,260	0.105	0.059	0.091
Tenure	16,260	6.449	6.967	4.000
CEO	16,260	0.788	0.409	1.000

Panel B. Correlations Matrix with Spearman (Pearson) Correlations on the Upper (Lower) Diagonal

	Twitter	*Comp*	*Size*	*ROA*	*MTB*	*Return*	*RetVolt*	*Tenure*	*CEO*
Twitter		0.02*	-0.03***	0.00	0.06***	0.03***	0.00	0.05***	0.03***
Comp	0.02*		0.61***	0.16***	0.12***	0.10***	-0.26***	0.10***	0.20***
Size	-0.02**	0.52***		-0.01	-0.17***	0.02**	-0.39***	-0.08***	-0.11***
ROA	0.01	0.16***	0.13***		0.61***	0.19***	-0.25***	0.00	-0.01
MTB	0.07***	0.02*	-0.21***	0.35***		0.33***	-0.20***	0.04***	0.02**
Return	0.03***	0.05***	-0.03***	0.19***	0.25***		-0.14***	0.04***	0.00
RetVolt	-0.01	-0.20***	-0.32***	-0.34***	-0.13***	0.03***		-0.01	0.02*
Tenure	0.03***	0.00	-0.08***	0.01	0.03***	0.03***	-0.02*		0.45***
CEO	0.03***	0.17***	-0.11***	0.00	0.04***	0.01	0.01	0.29***	

This table presents descriptive statistics (panel A) and correlations for variables (panel B) used in the empirical analysis. The variables are defined as follows: *Twitter* is an indicator variable, taking the value of 1 if a manager has an active Twitter account in place by the end of year t and 0 otherwise. *Comp* is the natural logarithm of the total annual compensation a manager obtains in a given year. The annual compensation includes the manager's salary, bonuses, other annual compensation, the total value of restricted stock granted, the fair value of stock options granted, long-term incentive payouts, and all other pay. *Size* is the natural logarithm of total assets in place. *ROA* is the income before extraordinary items scaled by total assets. *MTB* is the market value divided by the book value of the firm's asset. *Return* is the annual stock return calculated using monthly returns from CRSP. *RetVolt* is the standard deviation of a firm's stock return. *Tenure* is the number of years the manager has been a CEO. *CEO* is an indicator variable, taking the value of 1 if a manager is currently serving as a CEO and 0 otherwise. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 two-tailed levels, respectively.

Table 2 Executive Compensation and Twitter Activity

Panel A. Baseline Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Var. =	*Comp*						
	OLS					EB	
	Coeff. (*t*-stat.)	Coeff. (*t*-stat.)	Coeff. (*t*-stat.)	Coeff. (*t*-stat.)	Coeff. (*t*-stat.)	Coeff. (*t*-stat.)	Coeff. (*t*-stat.)
Twitter	**0.172*****	**0.190*****	**0.191*****	**0.095****	**0.096****	**0.214*****	**0.140*****
	(3.12)	**(3.61)**	**(3.63)**	**(2.28)**	**(2.29)**	**(6.00)**	**(4.25)**
Twitter_Firm			-0.026		-0.010		
			(-1.20)		(-0.43)		
Size	0.348***	0.354***	0.354***	0.299***	0.299***	0.394***	0.323***
	(12.53)	(13.01)	(13.05)	(12.23)	(12.23)	(8.19)	(5.17)
ROA	0.487***	0.451***	0.452***	0.474***	0.474***	0.390	0.365
	(5.51)	(5.26)	(5.24)	(4.65)	(4.64)	(1.56)	(1.39)
MTB	0.094***	0.098***	0.098***	0.077***	0.077***	0.064*	0.019
	(6.01)	(6.69)	(6.69)	(5.73)	(5.73)	(1.97)	(0.32)
Return	0.068***	0.061***	0.062***	0.071***	0.072***	0.091***	0.130***
	(3.30)	(3.13)	(3.17)	(3.59)	(3.59)	(3.49)	(2.90)
RetVolt	-0.517**	-0.458**	-0.456**	-0.419**	-0.418**	-0.820**	-0.918**
	(-2.68)	(-2.67)	(-2.67)	(-2.23)	(-2.23)	(-2.54)	(-2.31)
Tenure	0.001	0.001	0.001	-0.022*	-0.022*	0.003	0.012
	(0.13)	(0.14)	(0.14)	(-2.00)	(-2.00)	(0.56)	(0.42)
CEO	0.626***	0.627***	0.627***	0.528***	0.528***	0.521***	0.491***
	(25.94)	(26.18)	(26.22)	(18.23)	(18.23)	(11.59)	(11.88)
Firm FE	Yes	Yes	Yes	No	No	Yes	No
Year FE	Yes	No	No	Yes	Yes	No	Yes
Industry x Year FE	No	Yes	Yes	No	No	Yes	No
Manager FE	No	No	No	Yes	Yes	No	Yes
N	16,138	16,138	16,138	16,016	16,016	16,138	16,016
Adj. R-sq.	0.73	0.73	0.73	0.76	0.76	0.86	0.86

This Panel reports the baseline results based on Model (1). Columns (1)–(5) report estimation results based on OLS. Columns (6) and (7) report the estimation results based on the entropy balancing (EB) method. *t*-statistics are based on robust standard errors corrected for heteroscedasticity and clustered at the industry level. $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 2 (Cont'd)

Panel B. Trend and Change Specifications

	(1)	(2)
Dep. Var. =	*Comp*	
	OLS	GMM
	Coeff. (*t*-stat.)	Coeff. (*t*-stat.)
Pre2	**0.088**	
	(1.32)	
Pre1	**0.001**	
	(0.02)	
Post0	**0.113***	
	(1.83)	
Post1	**0.221*****	
	(3.33)	
Post2+	**0.169****	
	(2.57)	
Twitter		**0.072***
		(1.90)
Lag_Comp		0.189***
		(6.52)
Size	0.354***	0.260***
	(13.07)	(8.48)
ROA	0.448***	0.355***
	(5.20)	(4.10)
MTB	0.098***	0.082***
	(6.69)	(4.91)
Return	0.061***	0.031*
	(3.13)	(1.91)
RetVolt	-0.467***	0.032
	(-2.72)	(0.18)
Tenure	0.001	-0.008
	(0.14)	(-1.37)
CEO	0.627***	0.415***
	(26.25)	(14.04)
Firm FE	Yes	Yes
Industry x Year FE	Yes	Yes
N	16,138	12,845
Adj. R-sq.	0.73	--

This panel reports the results of trend and other falsifiable analyses. *Pre<j> (Post<j>)* is an indicator variable that takes the value of 1 for *j* years before (after) a manager opens her Twitter account and 0 otherwise. *Post2+* is a dummy variable that takes the value of 1 if it is two years or more after a manager opens her Twitter account. *Lag_Comp* is the *Comp* in year t-1. All other variables are defined in Table 1. *t*-statistics are based on robust standard errors corrected for heteroscedasticity and clustered at the industry level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 2 (Cont'd)

Panel C. Instrumental Variable (IV) Analysis

	(1)	(2)
Dep. Var. =	*Comp*	
	Coeff. (z-stat.)	Coeff. (z-stat.)
^Twitter	**0.217****	**0.193****
	(2.56)	**(2.26)**
Size	0.199**	0.199**
	(2.47)	(2.47)
ROA	0.748***	0.748***
	(4.21)	(4.21)
MTB	0.159***	0.159***
	(6.04)	(6.04)
Return	0.050**	0.050**
	(2.46)	(2.46)
RetVolt	0.196	0.194
	(0.45)	(0.45)
Tenure	-0.002	-0.002
	(-0.36)	(-0.36)
CEO	0.599***	0.599***
	(17.96)	(17.95)
Firm FE	Yes	Yes
Industry x Year FE	Yes	Yes
Hansen J Stat. (p-value)	0.808	0.765
Cragg-Donald Wald F Stat.	916.554	899.062
N	16,138	16,138
Centered R-sq.	0.17	0.17

This panel reports the results of instrumental variable (IV) analysis. *Twitter_Popularity* is the percentage of managers on our final list who use Twitter accounts in a state in the beginning of a year. We re-estimate our baseline model using the instrumented value of *Twitter*, which we label ^*Twitter*. Column (1) reports the results of our second-stage regression based on a two-stage approach and the Lewbel (2012) procedure to generate instrumental variables other than *Twitter_Popularity*. Column (2) reports the results of our third-stage regression based on Wooldridge's (2010) three-stage approach and the Lewbel (2012) procedure to generate instrumental variables other than *Twitter_Popularity*. $t(z)$-statistics are based on robust standard errors corrected for heteroscedasticity and clustered at the industry level. $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 2 (Cont'd)

Panel D: Effect of Twitter Audience

	(1)	(2)
Dep. Var. =	*Comp*	
	Number of followers	Focused following
	Coeff. (t-stat.)	Coeff. (t-stat.)
High_Twitter	**0.329*****	**0.251*****
	(5.96)	**(4.73)**
Low_Twitter	**0.116***	**0.127***
	(1.94)	**(1.98)**
Size	0.353***	0.354***
	(13.02)	(12.99)
ROA	0.451***	0.450***
	(5.28)	(5.24)
MTB	0.098***	0.098***
	(6.73)	(6.64)
Tenure	0.061***	0.061***
	(3.14)	(3.11)
Return	-0.458**	-0.458**
	(-2.67)	(-2.66)
RetVolt	0.001	0.001
	(0.15)	(0.14)
CEO	0.626***	0.626***
	(26.15)	(26.11)
Firm FE	Yes	Yes
Industry x Year FE	Yes	Yes
N	16,138	16,138
Adj. R-sq.	0.73	0.73
Test of *High_Twitter* = *Low_Twitter*:		
F-stat.	6.35**	3.07*

This panel reports the effect of Twitter following. *High (Low)_Twitter* equals 1 if a manager with Twitter in place (*Twitter*=1) obtains high (low) following from the Twitter users and 0 otherwise. We define a high (or low) Twitter following based on (1) the number of followers of a Twitter manager (Column 1), and (2) whether a Twitter manager's followers are focused (Column 2). t-statistics are based on robust standard errors corrected for heteroscedasticity and clustered at the industry level. $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 3 Comparative Statics

Panel A. Attention Deficit

	(1)	(2)	(3)
Dep. Var. =		*Comp*	
Attention_Deficit =	Not a CEO	Low Google Search Frequency	Shorter Executive Experience
	Coeff. (*t*-stat.)	Coeff. (*t*-stat.)	Coeff. (*t*-stat.)
Attention_Deficit* × *Twitter	**0.514*****	**0.173****	**0.101***
	(3.07)	**(2.51)**	**(1.92)**
Twitter	**0.205*****	**0.134*****	**0.106****
	(5.35)	**(3.00)**	**(2.08)**
Attention_Deficit	-0.567***	-0.044**	-0.027
	(-6.58)	(-2.31)	(-0.94)
Size	0.330***	0.354***	0.353***
	(10.42)	(12.87)	(13.00)
ROA	0.526***	0.451***	0.451***
	(5.67)	(5.19)	(5.27)
MTB	0.100***	0.098***	0.098***
	(6.49)	(6.78)	(6.71)
Return	0.063***	0.062***	0.061***
	(3.22)	(3.14)	(3.12)
RetVolt	-0.423**	-0.457**	-0.457**
	(-2.31)	(-2.65)	(-2.67)
Tenure	0.013***	0.001	0.000
	(2.85)	(0.11)	(0.03)
CEO		0.625***	0.625***
		(26.29)	(26.44)
Firm FE	Yes	Yes	Yes
Industry x Year FE	Yes	Yes	Yes
N	16,138	16,138	16,138
Adj. R-sq.	0.69	0.73	0.73

This panel reports the results of comparative statics tests based on attention deficit and education. *Attention_Deficit* is an indicator variable equal to 1 if either (1) a manager is not the CEO, (2) the Google search volume index of a manager is lower than the cut-off value for the top tercile, or (3) the number of years working in a firm is lower than the cut-off value for the top tercile, and 0 otherwise. All three variables are based on the status in the year before the initiation of the activity on Twitter. All other variables are defined in Table 1. *t*-statistics are based on robust standard errors corrected for heteroscedasticity and clustered at the industry level. $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 3 (Cont'd)

Panel B. Tweeting for Attention

	(1)	(2)	(3)
Dep. Var. =		*Comp*	
	Number of tweets	Usage of hashtags	Frequency of directed tweets
	Coeff. (*t*-stat.)	Coeff. (t-stat.)	Coeff. (*t*-stat.)
High_Attention_Twitter	**0.331*** **	**0.261*** **	**0.301*** **
	(12.34)	**(4.48)**	**(5.07)**
Low_Attention_Twitter	**0.186*** **	**0.180*** **	**0.179*** **
	(4.96)	**(3.60)**	**(3.54)**
Size	0.353***	0.354***	0.353***
	(12.99)	(13.02)	(13.02)
ROA	0.451***	0.451***	0.450***
	(5.25)	(5.25)	(5.25)
MTB	0.098***	0.098***	0.098***
	(6.61)	(6.68)	(6.68)
Return	0.061***	0.062***	0.061***
	(3.13)	(3.13)	(3.14)
RetVolt	-0.459**	-0.459**	-0.459**
	(-2.67)	(-2.67)	(-2.67)
Tenure	0.001	0.001	0.001
	(0.15)	(0.14)	(0.14)
CEO	0.626***	0.627***	0.627***
	(26.16)	(26.17)	(26.17)
Firm FE	Yes	Yes	Yes
Industry x Year FE	Yes	Yes	Yes
N	16,138	16,138	16,138
Adj. R-sq.	0.73	0.73	0.73
Test of *High_Attention_Twitter* = *Low_Attention_Twitter:*			
F-stat.	33.04***	4.73*	7.48***

This panel reports cross-sectional tests of the attention of Twitter users. *High_Attention_Twitter* (*Low_ Attention_Twitter*) equals 1 if a manager with Twitter in place (*Twitter*=1) obtains high (low) attention from Twitter users and 0 otherwise. We define high (or low) attention as (1) the number of tweets made by a manager in a year (column (1)), (2) the average number of hashtags ("#") used in a tweet made by a manager in a year (column (2)), and (3) the number of directed tweets (column 3). All other variables are defined in Table 1. *t*-statistics are based on robust standard errors corrected for heteroscedasticity and clustered at the industry level. ∗, ∗∗, and ∗∗∗ indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 3 (Cont'd)

Panel C. Prior Compensation Level

	(1)	(3)
Dep. Var. =	*Comp*	
	Low	Others
	Coeff. (*t*-stat.)	Coeff. (*t*-stat.)
Twitter	**0.379*** **	**0.041**
	(6.13)	**(0.94)**
Size	0.321***	0.332***
	(4.54)	(12.84)
ROA	0.765***	0.375***
	(2.81)	(4.90)
MTB	0.042*	0.116***
	(1.76)	(8.98)
Return	0.157***	0.029
	(5.09)	(1.64)
RetVolt	-0.890***	-0.172
	(-3.95)	(-1.03)
Tenure	-0.015	0.006***
	(-1.09)	(3.16)
CEO	0.690***	0.549***
	(12.31)	(27.31)
Firm FE	Yes	Yes
Industry x Year FE	Yes	Yes
N	4,674	11,330
Adj. R-sq.	0.68	0.72

This panel presents the results of comparative statics tests based on prior pay level. We divide our sample into terciles, "Low," and "Others," based on the residual value from the following model. "Low" represent the bottom tercile and "Others" represent the middle and upper terciles. The baseline model is

$$Comp = \alpha_0 + \alpha_1 Size + \alpha_1 ROA + \alpha_2 MTB + \alpha_3 Return + \alpha_4 RetVolt + \alpha_5 Tenure + \alpha_6 CEO + Year\ FE + \varepsilon$$

All other variables are defined in Table 1. *t*-statistics are based on robust standard errors corrected for heteroscedasticity and clustered at the industry level. $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 3 (Cont'd)

Panel D. Systematic Process

Dep. Var. =	*Comp*
	Coeff. (*t*-stat.)
NoConsult* × *Twitter	**0.310***
	(1.81)
Twitter	**0.176*** **
	(3.32)
NoConsult	0.015
	(0.98)
Size	0.354***
	(13.06)
ROA	0.449***
	(5.29)
MTB	0.099***
	(6.79)
Return	0.061***
	(3.12)
RetVolt	-0.458**
	(-2.67)
Tenure	0.001
	(0.15)
CEO	0.627***
	(26.20)
Firm FE	Yes
Industry x Year FE	Yes
N	16,138
Adj. R-sq.	0.73

This panel reports the results of comparative statics tests based on compensation consulting. *NoConsult* is an indicator variable equal to 1 if the current employer has not hired a compensation consultant, and 0 otherwise. This variable is calculated based on the status in the year before the initiation of the activity on Twitter. All other variables are defined in Table 1. *t*-statistics are based on robust standard errors corrected for heteroscedasticity and clustered at the industry level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 3 (Cont'd)

Panel E. Job Mobility

	(1)
Dep. Var. =	*Comp*
	Coeff. (*t*-stat.)
High_Mobility* × *Twitter	**0.153****
	(2.25)
Twitter	**0.076**
	(0.98)
High_Mobility	0.026
	(0.33)
Size	0.353***
	(12.98)
ROA	0.451***
	(5.25)
MTB	0.098***
	(6.74)
Return	0.061***
	(3.08)
RetVolt	-0.457**
	(-2.65)
Tenure	0.001
	(0.14)
CEO	0.627***
	(26.17)
Firm FE	Yes
Industry x Year FE	Yes
N	16,138
Adj. R-sq.	0.73

This panel reports the results of comparative statics tests based on job mobility. *High_Mobility* is an indicator variable that represents weak non-compete provision enforcement. *High_Mobility* equals 1 if a manager works for a firm located in a state with the score of the enforcement index for non-compete covenants (reported in Ertimur et al. (2017)) is below 5 and 0 otherwise. All other variables are defined in Table 1. *t*-statistics are based on robust standard errors corrected for heteroscedasticity and clustered at the industry level. ∗, ∗∗, and ∗∗∗ indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 4 Other Career Outcomes and Twitter Activity

	(1)	(2)	(3)
Dep. Var. =	*Seats*		*CEO*
	Private	Publicly listed	
	Coeff. (*t*-stat.)	Coeff. (t-stat.)	Coeff. (*t*-stat.)
Twitter	**-0.002**	**0.061***	**0.620*****
	(-0.05)	**(1.73)**	**(3.39)**
Size	-0.009	0.023**	-0.062
	(-0.68)	(2.32)	(-1.03)
ROA	-0.014	-0.041*	0.542***
	(-0.52)	(-1.93)	(3.50)
MTB	0.002	0.003	0.006
	(0.45)	(0.58)	(0.24)
Return	-0.006	-0.003	0.020
	(-1.08)	(-0.65)	(0.87)
RetVolt	0.094*	0.090**	0.319
	(1.68)	(1.98)	(1.07)
Tenure	0.012***	0.004***	0.080***
	(6.26)	(2.99)	(11.49)
CEO	0.165***	0.020**	
	(13.82)	(2.19)	
Firm FE	Yes	Yes	Yes
Industry x Year FE	Yes	Yes	Yes
N	16,138	16,138	16,138
Adj. R-sq.	0.62	0.65	0.11

This table examines the impact of Twitter activity on other aspects of manager welfare- or career-related outcomes: the probability of promotion to CEO, and number of directorship. Column (1) reports the estimation results of a CRE probit model. Columns (2) and (3) report the results based on Model (1) using the dependent variables *Seats*. *Seats* is measured by the natural logarithm of 1 plus the number of boards of public or private companies a manager serves on. All other variables are defined in Table 1. $t(z)$-statistics are based on robust standard errors corrected for heteroscedasticity and clustered at the industry level. $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% levels, respectively.

Appendix A Summary Statistics of the Entropy Balancing Procedure

	Tweeting Mangers			Non-Tweeting Managers					
				Before balancing			After balancing		
	Mean	Variance	Skewness	Mean	Variance	Skewness	Mean	Variance	Skewness
Size	7.159	3.073	0.616	7.716	2.820	0.186	7.146	3.072	0.638
ROA	0.046	0.012	-1.980	0.037	0.011	-2.256	0.046	0.013	-1.977
MTB	2.410	1.930	0.955	1.788	1.026	2.228	2.411	1.929	0.953
Return	0.253	0.173	0.899	0.163	0.219	1.120	0.253	0.173	0.897
RetVolt	0.100	0.002	1.342	0.105	0.004	1.726	0.100	0.002	1.353
Tenure	8.753	48.370	1.147	6.425	48.430	1.538	8.748	48.350	1.148
CEO	0.941	0.056	-3.738	0.787	0.168	-1.398	0.940	0.056	-3.718

Appendix B Some Examples of Tweets

Executive Name	Twitter Account	Tweet Date	Tweet Detail
Karl McDonnell	@Karl_McDonnell	8 Feb 2011	Just signed up for Twitter....looking forward to writing about all sorts of useless things....
Karl McDonnell	@Karl_McDonnell	24 Jan 2012	Great to hear @jack_welch and @SuzyWelch have joined Reuters and Fortune for a new weekly column. #leadership #management @fortune
Karl McDonnell	@Karl_McDonnell	1 Feb 2012	Chicago at sunset, looking north along Lake Michigan. #photography #landscapes
Karl McDonnell	@Karl_McDonnell	5 Oct 2012	@darrenrovell Thanks for sharing. GREAT video. #mlb #baseball #playoffs
Mark T. Bertolini	@mtbert	15 Sep 2009	@MsLaurenRae sorry i missed the ride!
Mark T. Bertolini	@mtbert	14 Oct 2011	@FdoAguirreCEO one game at a time! #Tigers #ALCS
Mark T. Bertolini	@mtbert	24 Jan 2012	Snow, snow and more snow...it's all over here USA! #Davos #WEF
Mark T. Bertolini	@mtbert	26 Feb 2012	Hey man, a very Happy Birthday to @TheClothier! All the blessings of family, friends and the Creator on this special day. Do good things:)
Patrick Decker	@PatrickKDecker	30 Aug 2014	Bang head against wall in Berlin! Great day of galleries. #berlin
Patrick Decker	@PatrickKDecker	13 Sep 2014	@SwimOutDaily thanks Angel! And here's to swimming out to meet our ships rather than waiting for them to come to us!!
Patrick Decker	@PatrickKDecker	4 Oct 2014	Nothing like #loud neighbors inviting you to a #Housewarming #party that drowns out your stereo in your own home. Very nice touch.
Patrick Decker	@PatrickKDecker	14 Apr 2014	#RIP a #magician #whenamanlovesawoman @NYMag: Soul singer Percy Sledge has died at 73