Online Appendix:

Tweeting Away Firm Value? How Investors Evaluate CEOs' Use of Social Media

Online Appendix A. Details on our Machine Learning Method

In this study, we employ machine learning (ML) to classify a large set of tweets into three types. ML encompasses a set of data analysis methods that enable computers to learn from data and make predictions or decisions without being explicitly programmed for each task.

To categorize the tweets, we use a type of ML known as supervised learning. Supervised learning involves training an algorithm using a labeled dataset, which it then applies to predict outcomes for new, unseen data. In our study, the training dataset consists of 34,585 tweets, which our research assistants manually classified into three categories: Type-1, Type-2, and Type-3 tweets.

We divide the manually labeled dataset into two subsets: 70% for training the model and 30% for testing. The training set is used to develop the machine learning model, while the testing set evaluates the model's performance on unseen data. This procedure ensures that the model generalizes well to new data and not just 'memorizes' the data in the training set.

We experiment with five widely-used classification algorithms: Logistic Regression (LR), Naïve Bayes (NB), Random Forest (RF), Support Vector Machine (SVM), and Extreme Gradient Boosting (XGBoost).

1. **Logistic Regression (LR)** is a statistical technique for predicting binary outcomes. In our context, it predicts whether a tweet belongs to a specific category.
2. **Naïve Bayes (NB)** is a classification method based on Bayes' Theorem, assuming independence between features. It predicts class membership by estimating the likelihood of features occurring in each class.
3. **Random Forest (RF)** is an ensemble learning method that combines multiple decision trees to produce a more accurate prediction. It predicts the category by taking the

majority vote from the individual trees.

4. **Support Vector Machine (SVM)** is a versatile machine learning model that can perform linear and non-linear classification. It identifies the optimal hyperplane that best separates the categories.
5. **Extreme Gradient Boosting (XGBoost)** is a highly efficient implementation of the gradient boosting algorithm. It iteratively builds models that correct the errors of prior models to enhance prediction accuracy.

Among these algorithms, SVM delivered the best performance and was therefore chosen to classify the remaining 216,349 tweets. The other algorithms yielded similar results (available upon request), indicating the robustness of our machine learning approach.

Online Appendix B. Control Variable Definitions

The following CEO-level control variables are constructed using data from the Execucomp database: *CEO Age* is the age of the CEO. *CEO Tenure* is the number of years the CEO has served as CEO. *Male CEO* is an indicator set to one if the CEO is male. *Ln(Total Compensation)* is the natural logarithm of total compensation and calculated within EXEUCOMP as Ln(TDC1).

Extravert is the CEO's level of extraversion score from Green, Jame and Lock (2019). We obtain the extraversion scores from Green et al.

Inst. Holdings is the proportion of shares held by institutional investors as of the most recent calendar quarter-end in the SEC 13F holdings data, which we access through the LSEG database.

The ensuing variables are all constructed using data from the COMPUSTAT database: *Size* is the natural logarithm of the firm's book value of assets as of the most recent fiscal year-end, calculated within COMPUSTAT as Ln(AT). *Cash Flow* captures how much cash the firm has on hand and is calculated as ([OIBDP−XINT−TXT−CAPX]/AT). *ROA* measures the accounting profitability of the firm and is calculated as (OIBDP/AT). *Leverage* measures how much debt the firm has on its books and is calculated as ([DLC+DLTT]/AT). *Dividend* measures how much of the profits the firm decides to pay as dividends to its investors and is calculated as ([DVC+DVP]/OIBDP). *Capital Expenditure* measures how much the firm invests in physical assets and is calculated as (CAPEX/AT). *R&D* measures how much the firm invests in research and development and is calculated as (XRD/AT). *Sales/Total Assets* is the annual sales scaled by the book value of total assets (SALE/AT). *Sales Growth* measures the growth in sales and is calculated as the percentage change in SALE. *Stock Returns* is the firm's buy-and-hold stock return over the previous year from CRSP. *Loss* is an indicator set to one if a firm has negative net income (OIBDP) in a given year, and zero otherwise. *Z-Score* is the Altman Z-score predicting whether a company is headed for bankruptcy (Altman, 1968), calculated as:

$$ZScore = 3.3 \times \frac{Earnings\ before\ Interest\ and\ Tax}{Total\ Assets} + 1.2 \times \frac{Working\ Capital}{Total\ Assets} + 1 \times \frac{Sales}{Total\ Assets} +$$

$$0.6 \times \frac{Market\ Value\ of\ Equity}{Total\ Liabilities} + 1.4 \times \frac{Retained\ Earnings}{Total\ Assets},$$

and within COMPUSTAT as:

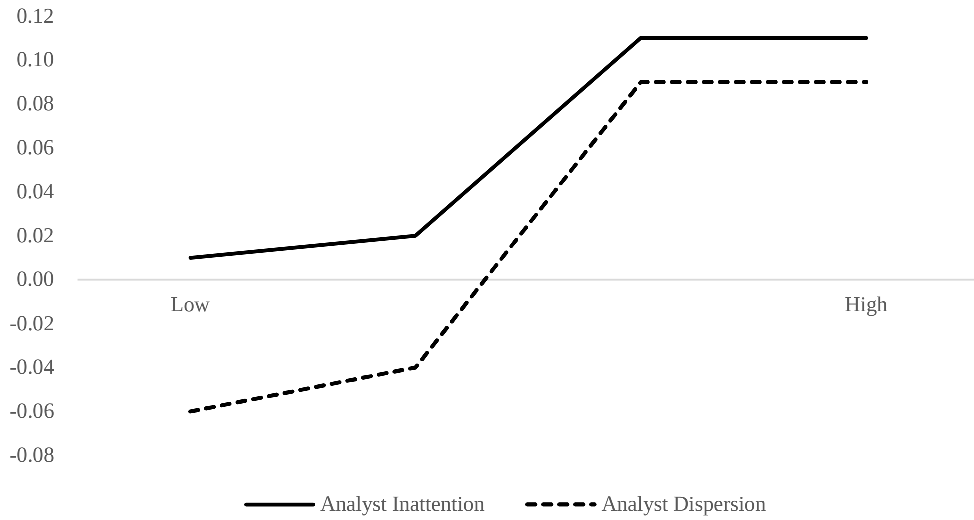
$$ZScore = 3.3 \times \frac{OIADP}{AT} + 1.2 \times \frac{ACT - LCT}{AT} + 1 \times \frac{SALE}{AT} + 0.6 \times \frac{PRCC_C \times CSHO}{DLTT + DLC} + 1.4 \times \frac{RE}{AT}.$$

The *E-Index* is the number of anti-takeover provisions a firm has, with each provision assigned one point, resulting in a score between 0 and 6 (Bebchuk, Cohen, and Ferrell, 2009). The six provisions are: staggered boards, limits to shareholder bylaw amendments, limits to charter amendments, supermajority requirements for mergers, supermajority requirements for charter amendments, and poison pills. A higher E-index score indicates greater managerial entrenchment. We obtain the E-Index score through the ISS ESG database.

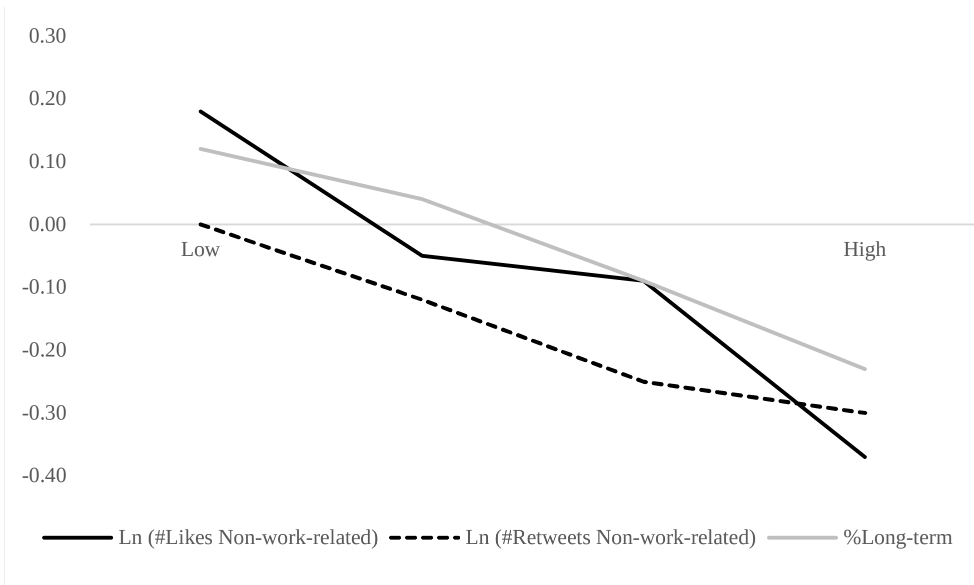
Ln(#News Articles) is the natural logarithm of the number of news articles for the corresponding firm in that year appearing in the Dow Jones Newswires, which we access through the RavenPack database.

Online Appendix C. Margin Plots for Moderating Effects

Panel A. Corporate Communication Moderators



Panel B. CEO Distraction Moderators



Online Appendix D. Robustness

	(1) Excluding Elon Musk	(2) Double Clustering	(3) Lagged Xs	(4) Winsorization
Ln(#Work-Related Tweets)	0.10	0.10	0.09	0.07
	(0.02)	(0.07)	(0.03)	(0.07)
Ln(#Non-Work-Related Tweets)	-0.08	-0.09	-0.06	-0.07
	(0.11)	(0.07)	(0.16)	(0.16)
Controls	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
# Obs.	23,020	23,030	22,166	23,030
Adj. R^2	0.706	0.706	0.679	0.670

Online Appendix E. Survey of Institutional Investors

E1. Methodology

Our online survey begins with two text entry questions:

QBenefits: "*You likely have encountered tweets that a CEO sent from his/her personal Twitter account. In your opinion, what are some possible benefits of such personal Twitter activity to the firm that employs the CEO? Please list one to three possible benefits or leave everything blank if you think there are no benefits to the firm and simply move on to the next question.*"

QDrawbacks: "*Again, you likely have encountered tweets that a CEO sent from his/her personal Twitter account. In your opinion, what are some possible drawbacks of such personal Twitter activity to the firm that employs the CEO? Please list one to three possible drawbacks or leave everything blank if you think there are no drawbacks to the firm and simply move on to the next question.*"

We use open-ended text entry questions to minimize our influence in the data-generating process. We compile the perceived benefits and group common responses. We apply the same procedure to the perceived drawbacks. Our next section describes the "common-response categories" and provides representative examples.

After querying institutional investors on the perceived benefits and drawbacks of CEOs' Twitter use, we conclude the survey with two multiple-choice questions:

QNetEffect: "*All in all, would you say that the benefits (drawbacks) outweigh the drawbacks (benefits)? Please choose one of the five options below:*

(a) The drawbacks strongly outweigh the benefits

(b) The drawbacks somewhat outweigh the benefits

(c) The drawbacks match the benefits

(d) The benefits somewhat outweigh the drawbacks

(e) The benefits strongly outweigh the drawbacks"

QLikelihood_Investing: *"Relatedly, consider a CEO who regularly tweets from his/her personal Twitter account. Would such activity make it more or less likely that you invest in the corresponding stock or have no effect at all?*

(a) Make it much less likely

(b) Make it somewhat less likely

(c) Have no effect at all

(d) Make it somewhat more likely

(e) Make it much more likely"

In the results section, we report the proportions of investors selecting each option. We assign scores to each response: -2 for option "(a)", -1 for option "(b)", 0 for option "(c)", +1 for option "(d)", and +2 for option "(e)". We calculate the average scores for both **QNetEffect** and **QLikelihood_Investing**, weighted by the proportion of investors selecting each option. Negative scores indicate that, on average, investors perceive the drawbacks to outweigh the benefits and that CEOs' Twitter activity reduces the likelihood of investing in the stock. Positive scores suggest that the benefits outweigh the drawbacks, leading to an increased likelihood of investment.

E2. Results

The perceived benefits that our institutional investors list in response to question QBenefits largely fall into two broad categories:

1. Useful information to investors, and
2. Greater customer and investor awareness.

Regarding the first category, many investors note that CEO tweets could provide incremental, value-relevant information (e.g., “forum to disseminate information that you won’t see in statements,” “learn how the CEO thinks,” “timely CEO thinking,” “Unfiltered”) and thereby enhance transparency (e.g., “More transparent,” “transparency”).

Investors also suggest that CEOs can use Twitter to draw “positive” attention to them- selves and their company and products, thereby increasing customer and investor reach. Representative quotes include “humanizes/familiarizes the CEO,” “draw attention to the company/increase awareness,” “enhanced name recognition/association,” “visibility,” and “word of mouth.”

The perceived drawbacks largely fall into the following three broad categories:

1. Potential market manipulation charges,
2. The risk of antagonizing customers and investors, and
3. Seemingly flippant corporate leadership.

Regarding the first category, most institutional investors in our sample note that being active on Twitter could lead CEOs to inadvertently violate disclosure rules or be accused of market manipulation by financial regulators (e.g., “Inadvertent non-public information leak,” “insider information,” “market manipulation,” “potential for inside info spill,” “regulatory risk”).

Beyond the potential penalties accompanying the violation of disclosure rules and charges of market manipulation, any investigation by financial regulators poses a significant distraction and may prevent corporate executives from focusing on their core responsibilities. This lack of focus could lead to suboptimal decision-making and harm firms' value.

Regarding the second category, while CEOs' Twitter activity may draw "positive" attention to the corresponding companies and products, many institutional investors in our sample highlight that tweets can easily antagonize customers and shareholders (e.g., "alienate," "Bad press," "contentious views," "offensive to some recipients," "political divisiveness," "reputational risk," "unintended consequences").

Finally, numerous institutional investors suggest that any active Twitter use, despite the legal, reputational, and financial risks, raises concerns about the CEO's judgment and leadership qualities. Quotes include "arrogant," "I'm more important than you," "impulsive," "personal," "pontification," "self-serving," and "their personal agenda," among others.

Table E-2 shows that, on balance, the perceived drawbacks outweigh the perceived benefits to the investors in our sample. The average score for **QNetEffect** is -0.46, with a median of -1. The average score for **QNetEffect** is especially negative for investors aged 55 years or older (-0.77) and, similarly, for investors with 20 or more years of experience (-0.49). The average score is slightly more negative for investors managing assets worth $2.5 billion or more (-0.50) compared to investors managing less than $2.5 billion (-0.44).

On balance, CEOs' Twitter activity decreases the likelihood that institutional investors will invest in the corresponding stock. 19% of our survey participants report that regular Twitter activity would make it "much less likely" that they will invest in the stock, while 30% state that regular Twitter activity would make it "somewhat less likely" that they will invest.

By comparison, only 18% suggest that Twitter activity would make it "somewhat more likely" that they will invest. None of the institutional investors in our sample report that Twitter activity would make it “much more likely” that they will invest in the corresponding stock. The average score for **QLikelihood_Investing** is -0.50. Once again, the average score is particularly negative for older investors (-0.75) and those with more experience (-0.61). It is slightly more negative for investors managing more than $2.5 billion in assets (-0.56) compared to those managing less than $2.5 billion (-0.47).

Online Appendix Table E-1: Summary of Survey Responses

		Number
Q1:	“How old are you?”	
	25-34	2
	35-44	20
	45-54	29
	55-64	35
	65+	13
	Prefer not to say	1
Q2:	“Please indicate your gender”	
	Female	10
	Male	87
	Prefer not to say	3
Q3:	“Approximately how many years have you worked as a wealth manager/fund manager?”	
	< 10 years	3
	10-19 years	28
	20-29 years	50
	30 years +	19
Q4:	“What is your company’s overall assets under management (AUM)?”	
	$10 million to $99.9 million	19
	$100 million to $249.9 million	25
	$250 million to $999.9 million	15
	$1 billion to $2.49 billion	7
	$2.5 billion+	34

Online Appendix Table E-2: Summary of Survey Responses

QNetEffect: "All in all, would you say that the benefits (drawbacks) outweigh the drawbacks (benefits)? Please choose one of the five options below."

	"The drawbacks strongly outweigh the benefits"	"The drawbacks somewhat outweigh the benefits"	"The drawbacks match the benefits"	"The benefits somewhat outweigh the drawbacks"	"The benefits strongly outweigh the drawbacks"	Average [Median] Score
	(1)	(2)	(3)	(4)	(5)	(6)
Full Sample (N=100)	30.0%	21.0%	20.0%	23.0%	6.0%	-0.46 [-1.00]
54 years or younger (N=51)	17.7%	23.5%	23.5%	25.5%	9.8%	-0.14 [0.00]
55 years or older (N=48)	41.7%	18.8%	16.7%	20.8%	2.1%	-0.77 [-1.00]
Female (N=10)	10.0%	30.0%	20.0%	40.0%	0.0%	-0.10 [0.00]
Male (N=87)	32.2%	20.7%	19.5%	20.7%	6.9%	-0.51 [-1.00]
19 years of experience or less (N=31)	22.6%	25.8%	22.6%	25.8%	3.2%	-0.39 [0.00]
20 years of experience or more (N=69)	33.3%	18.8%	18.8%	21.7%	7.3%	-0.49 [-1.00]
Less than $2.5 billion in AUM (N=66)	28.8%	21.2%	22.7%	19.7%	7.6%	-0.44 [-0.50]
$2.5 billion in AUM or more (N=34)	32.4%	20.6%	14.7%	29.4%	2.9%	-0.50 [-1.00]

Online Appendix Table E-2. Continued

QLikelihood_Investing: "Relatedly, consider a CEO who regularly tweets from his/her personal Twitter account. Would such activity make it more or less likely that you invest in the corresponding stock or have no effect at all?"

	"Make it much less likely" (1)	Make it somewhat less likely" (2)	"Have no effect at all" (3)	"Make it somewhat more likely" (4)	"Make it much more likely" (5)	Average [Median] Score (6)
Full Sample (N=100)	19.0%	30.0%	33.0%	18.0%	0.0%	-0.50 [0.00]
54 years or younger (N=51)	9.8%	29.4%	35.3%	25.5%	0.0%	-0.24 [0.00]
55 years or older (N=48)	27.1%	31.3%	31.3%	10.4%	0.0%	-0.75 [-1.00]
Female (N=10)	10.0%	20.0%	40.0%	30.0%	0.0%	-0.10 [0.00]
Male (N=87)	19.5%	31.0%	32.2%	17.2%	0.0%	-0.53 [-1.00]
19 years of experience or less (N=31)	16.1%	19.4%	38.7%	25.8%	0.0%	-0.26 [0.00]
20 years of experience or more (N=69)	20.3%	34.8%	30.4%	14.5%	0.0%	-0.61 [-1.00]
Less than $2.5 billion in AUM (N=66)	18.2%	31.8%	28.8%	21.2%	0.0%	-0.47 [-0.50]
$2.5 billion in AUM or more (N=34)	20.6%	26.5%	41.2%	11.8%	0.0%	-0.56 [0.00]

Online Appendix References

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