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Executive Tweets

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Abstract. We explore the tweeting behavior of S&P 1500 firms' chief executive officers and chief financial officers and its market reactions from 2011 to 2018. Executives post a variety of content on Twitter, with slightly less than half of their tweets relating to business matters. We find that most executive tweets do not elicit market reactions. However, the subset of executive tweets about financial information appears to be associated with market reactions incremental to the responses to firm-issued tweets. These reactions coincide with increases in trading volume and retail investor activity. To assess whether market responses are driven by new information or by changes in perceived credibility, we develop an innovative machine-learning-based measure of content similarity between executive and firm tweets. We find stronger investor reactions when executive financial tweets are more similar to prior firm tweets, consistent with the perceived credibility mechanism. At the same time, executive financial tweets also generate market reactions in the absence of firm disclosures, supporting the new information mechanism.

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1. Introduction

Social media has fundamentally transformed the way information is disseminated in capital markets. Among various platforms, the common perception of Twitter is that its followers are more likely to be present or potential investors, whereas other outlets such as Facebook and LinkedIn are used primarily for social interaction or professional networking. Twitter (now X) has thus emerged as the most popular venue for instantaneous information exchange between firms and individuals.¹ From investors parsing brief corporate announcements to journalists and policymakers reacting to executive commentary, Twitter is now an integral part of the corporate information environment. Investors, executives, and firms all contribute to the discussions on the platform. Firms are highly active in sharing product launches, earnings updates, or sustainability initiatives. Well-known executives such as Richard Branson

(Virgin), Tim Cook (Apple), and Satya Nadella (Microsoft) have millions of followers, and their tweets often reach audiences that far exceed the traditional reach of firm press releases.

Social media has transformed the way firms engage with customers, investors, and capital markets, stimulating a growing body of research in accounting, finance, and marketing. A substantial literature shows that social media activity by both investors and firms affects market outcomes and investor attention. Studies on investor tweeting behavior document that the online dissemination of opinions and sentiments can shape short-term trading and stock price formation (Bollen et al. 2011, Sprenger et al. 2014, Curtis et al. 2016, Bartov et al. 2018, Campbell et al. 2023). On the corporate side, the emergence of Twitter reduces investors' search costs and improves liquidity by accelerating the dissemination of information (Blankespoor et al. 2014, 2020).

Firms use Twitter to amplify press releases (Blankespoor et al. 2014), respond to crises (Lee et al. 2015), and directly disseminate information to market participants (Jung et al. 2018, Crowley et al. 2024). Nekrasov et al. (2022) further highlight that the inclusion of visuals significantly increases investor attention. Collectively, these findings suggest that Twitter has evolved from a social network into a core channel of information dissemination in financial markets.

Given the natural connection between firms and executives, one might expect firms' and executives' tweets to generate similar market reactions. However, executives' online presence occupies a unique intersection between personal identity and corporate representation. Whereas firm tweets are subject to internal controls, legal reviews, and investor relations oversight, executives' personal accounts, in contrast, operate with fewer institutional constraints and greater flexibility.² Executive accounts can serve as authentic, unscripted channels that reveal executives' thinking, values, and, sometimes, their insider perspectives. Executives may tweet about industry trends, philanthropy, politics, and hobbies, while at times commenting on matters related to firm performance. This heterogeneity of content, combined with executives' perceived authority and credibility, raises important yet unanswered questions: When executives speak online, does the market respond? If so, which messages matter, and through what mechanisms? Our study provides comprehensive large-sample evidence on how executives use Twitter and how their tweets influence market behavior.

Early surveys of executives suggest that executives hesitate to adopt social media because participating is risky, it takes too much time, or they believe that disseminating information on social media has no measurable return on investment (Kwoh and Korn 2012, Weber Shandwick 2014). This resistance may suggest that executives were concerned about the potential legal consequences of posting on social media. Such concerns were addressed by the U.S. Securities and Exchange Commission (SEC) report issued on April 2, 2013 (U.S. Securities and Exchange Commission 2013). The report detailed the SEC's investigation into a post by Netflix chief executive officer (CEO) Reed Hastings on July 3, 2012, concluding that the 2008 SEC "Commission Guidance on the Use of Company Web Sites" (U.S. Securities and Exchange Commission 2008) applies to executives' social media posts and that it is not a violation of Regulation FD (Fair Disclosure) for executives to post investor-relevant information on social media. Despite the prominence of executives' Twitter accounts, we know little about how often executives tweet, what topics dominate their posts, how these differ from firm communications, and under what conditions markets respond, and how. There has been little systematic study of executive tweeting behavior, with only a handful of

exceptions. First, Chen et al. (2025) analyze annual patterns of executive tweets, distinguishing work-related from non-work-related content. They link the composition of these tweets to firm value (Tobin's Q) and find that work-related tweeting correlates positively with firm value, whereas nonwork tweets have the opposite effect, particularly when user engagement is high. Second, Mkrtchyan et al. (2024) show that markets react positively to CEO's activism-related posts and that career outcomes of CEOs are tied to their activism on Twitter.

In this study, we collect and assemble a novel data set of executive tweets spanning S&P 1500 CEOs and chief financial officers (CFOs) from 2011 to 2018. We identify 548 executives on Twitter during our sample, and in the final year of our sample, there are 436 executives active on the platform, representing firms with a combined market value of \$7 trillion. After restricting to executives whose firms are also on Twitter, our final panel covers more than 142,000 tweets from 433 executives and 4.7 million tweets from their corresponding firms. This scope allows us to comprehensively examine executive activity on Twitter. Using an unsupervised machine-learning algorithm (Zhao et al. 2011), we categorize executive tweets into three groups based on their content: financial tweets, which are directly related to firm financial matters; nonfinancial business tweets, which reference firm operations, products, or events; and other (nonbusiness) tweets, which cover personal, social, or miscellaneous topics.

Our descriptive evidence paints a nuanced picture that shows that executive tweeting is pervasive, and financial tweets are only a small portion of it. Executives mostly use Twitter as a personal communication outlet or for corporate branding, not as a channel for investor-relevant information. Specifically, we find that around 45% of executives' tweets relate to business matters, such as discussing customer meetings, industry conferences, and products. Of the business-related tweets, only 1.7% relate to financial matters. Nevertheless, the existence of so few financial tweets creates the possibility of significant market effects when they do occur.

We examine abnormal stock returns, trading volume, and retail trading behavior around the release of executive tweets while controlling for contemporaneous firm tweets. Our analyses reveal a clear asymmetry in market response. Most executive tweets generate no significant market reaction, suggesting that investors largely disregard personal posts or interpret them as distractions. Business-related but nonfinancial tweets likewise have negligible effects. However, the small set of financial tweets, for example, those directly related to firm performance or earnings guidance, appear to generate economically meaningful reactions. On average, unsigned (signed) daily abnormal return increases by 0.4% (0.2%) per financial tweet, accompanied by higher trading volume, retail trading volume, and retail buy-sell imbalances. In other

words, most executive tweets are market irrelevant, but the few financial ones matter. These findings suggest that the market can distinguish between different kinds of executive communication, reacting selectively to investor-relevant content. We then conduct an additional test splitting executive tweets by their underlying sentiment. Over half of the executive tweets in our sample are positive, whereas only 10% are negative. Our analyses show increased signed market return and retail buy–sell imbalance around positive and neutral executive financial tweets.

A natural concern is that executives might tweet in reaction to market movements as opposed to their tweets driving stock price changes. To address this concern, we separate out tweets posted before trading hours (from prior close to current open) from those posted during trading. We continue to find that financial tweets are followed by positive abnormal returns and volume changes even when posted before the market opens, that is, when executives could not observe same-day price movements. This temporal evidence mitigates the endogeneity concern and reinforces the interpretation that tweets themselves can trigger investor responses.

We then examine two potential, but not mutually exclusive, channels through which executive financial tweets elicit market reactions. First, executives may reveal investor-relevant information not yet disseminated elsewhere (new information mechanism). Given their privileged access to firm operations and strategy, subtle hints or confirmatory remarks can carry informational value. Second, even when executive tweets contain information already available elsewhere, such as on firm Twitter accounts, investors may regard statements directly from the executive as more credible (perceived credibility mechanism). Personal communication from a well-known executive can reinforce existing disclosures and thus reduce the uncertainty of the information signal.

Our analyses find support for both mechanisms. When executive financial tweets are unmatched by contemporaneous firm tweets, we observe increased abnormal returns and retail buy–sell imbalance, consistent with the new information mechanism. Yet even when executive tweets closely resemble preceding firm tweets, measured using semantic similarity via Google’s universal sentence encoder (USE; Cer et al. 2018), we detect significant market reactions, consistent with the perceived credibility mechanism. The latter finding is particularly interesting, as it suggests that not only does it matter what is said, but who says it. This perceived credibility mechanism aligns with social identity theory (Ashforth and Mael 1989) and research on trust formation (Lewicki and Bunker 1996), which posit that perceived interpersonal interaction fosters trust. On Twitter, followers may feel a parasocial connection

with executives, amplifying credibility. Survey and experimental evidence support this view. Elliott et al. (2018) show that individuals react more positively to negative news shared by executives’ social media accounts than by corporate accounts or websites, whereas Brandflog (2012) finds that 82% of Fortune 500 employees trust a firm more when its CEO is active on social media. Thus, executives’ tweets not only convey information but also signal accountability, magnifying their influence relative to firms’ tweets.

We conduct supplemental analyses to provide corroborating evidence and mitigate concerns of an alternative mechanism. Our cross-sectional analyses show that the new information mechanism appears to be stronger when retail trading is high, and the perceived credibility mechanism appears to be stronger when the executive or firm is more visible, or when retail investors have more interest in the firm. These patterns suggest that attention on the executives and firms plays a role in the mechanisms, consistent with executive identity driving the effects. To assess whether repeated dissemination drives our findings, we conduct a falsification test by matching each firm’s financial tweets with their prior tweets. We do not find a positive market response when firms repeat earlier content, implying that the unique identity of the executive as the poster, rather than repeated dissemination alone, drives observed effects.

Our study contributes to several strands of literature and carries broader implications for both academia and practice. First, we advance the literature on social media and information dissemination in capital markets by emphasizing the influence of individual executives. Whereas prior studies establish that firms’ social media disclosures can reduce information asymmetry and improve liquidity (Blankespoor et al. 2014, Lee et al. 2015), we show that the dynamics of executive communication differ markedly. Executives rarely tweet about material financial matters, but when they do, markets respond. Second, we enrich the emerging literature on executive communication and perceived credibility. By documenting that executive tweets that echo firm disclosures can enhance perceived credibility, we uncover a new channel through which executives shape market sentiment. This complements prior findings on CEO activism (Mkrtchyan et al. 2024) and work-related tweeting (Chen et al. 2025), extending the analysis to real-time market reactions. Third, we contribute methodologically by employing machine-learning classification and semantic similarity algorithms to categorize millions of tweets, setting a foundation for future text-based research on social media. Beyond these contributions to the academic literature, our findings have practical implications. For regulators, understanding how executives communicate via personal accounts is crucial for monitoring information dissemination and

potential selective disclosure. For firms, the results highlight the need for governance policies that balance authenticity with compliance risk. For investors, the evidence underscores that executive voices carry informational weight, albeit selectively.

2. Data and Methodology

2.1. Data and Sample Selection

Our sample spans the years 2011 through 2018, covering all S&P 1500 firms contained in the index during these years. Firm and executive accounts were identified manually in multiple phases: firm and CEO Twitter handles in September–October 2016, CFO Twitter handles in April 2017, and additional collection of all three handle types in May 2020 and April 2023.³ We validated accounts during each identification step. In total, we identified 1,635 firm accounts and 620 executive accounts, of which 548 executives had an account as CEO or CFO during our sample period.⁴ We collected most tweets in our sample using the Twitter application programming interface (API), and for accounts with more than 3,200 tweets in our initial collection, we purchased data from Gnip, a data provider and subsidiary of Twitter. Subsequent data were all collected via the Twitter API. Our financial, executive, and stock return data are from Compustat Fundamentals Quarterly, Execucomp, and the Center for Research in Security Prices (CRSP), respectively. To identify information events, we use the following sources: the

Institutional Brokers' Estimate System (I/B/E/S) for earnings announcement times, Capital IQ for earnings conference call times, and the Wharton Research Data Services (WRDS) SEC Analytics Suite for 10-K, 10-Q, and 8-K release times.

Sample construction is detailed in Table 1, panel A. We refine our full sample of executive accounts to ensure a consistent set of observations across our main tests. First, our final sample includes only trading days on which both an executive and his or her firm have already created Twitter accounts, so that it is possible for the executive to tweet and for us to control for firm activity on Twitter. Additionally, we require complete information to compute control variables and dependent variables from Compustat, CRSP, and Execucomp. After these restrictions, our main regression sample contains 376,445 executive-trading day observations, where 70.7% (29.8%) of observations in the sample are from CEOs (CFOs).⁵ Out of the 376,445 executive-trading day observations, executives posted a tweet on 35,622 of them, that is, on approximately 9.5% of all executive-trading day observations. This sample includes 142,560 tweets from 433 executives, as well as 4.7 million tweets from 379 firms. Appendix A shows the top firm and executive accounts by the number of tweets they have posted in our main regression sample. Because tweet counts are highly skewed, we note that the top two executives posted 45% of all tweets in our sample, and the top 10 executives posted

Table 1. Sample Construction

Panel A: Sample selection			
Sample steps	# of executive-trading day observations	# of firms	# of executives
S&P 1500 firms, 2012–2018	6,939,547	2,119	7,063
Less: Executive not on Twitter	(6,445,186)	(1,629)	(6,515)
Full sample	494,361	490	548
Less: Firm not on Twitter	(114,795)	(104)	(107)
Observations with both firm and executive on Twitter	379,566	386	441
Less:			
Missing executive control data	(170)	(1)	(1)
Observations missing financial control variables	(379)	(0)	(0)
Observations missing lagged market data	(2,569)	(5)	(6)
Singleton observations	(3)	(1)	(1)
Main regression sample	376,445	379	433
Panel B: Number of tweets by type			
Tweet types	By executives	By firms	
Financial tweets	1,139	15,121	
Nonfin business tweets	63,298	2,402,362	
Other tweets	78,123	2,295,416	
Total tweets	142,560	4,712,899	

Notes. Panel A presents the sample construction, detailing the number of observations at the executive-trading day level, as well as the number of unique firms and executives represented by the sample. Panel B shows the number of tweets included in the main regression sample.

63% of all tweets in our sample. A similar concentration occurs for firm accounts as well, with the top 10 firms accounting for 59% of all firm tweets in the sample. Accordingly, in all regressions, we include executive and firm fixed effects (FEs) to control for individual executive and firm behavior on social media, and we conduct additional sensitivity analysis related to individual executives in Section 5.2.

2.2. Measure Construction

A key feature of our data is that all tweets and information events are tracked to the second of the announcement. We standardize all data by assigning each tweet or event to trading days based on the trading time at the New York Stock Exchange. In our main market tests, we assign tweets to trading days that span the close of the previous trading day through the close of the current trading day. A timeline is presented in Online Appendix OA.1. We adjust all timestamps for differences in time zones and daylight savings time.

2.2.1. Twitter Measures. Our primary measures are counts of the tweets posted by executives and firms on trading days or parts of trading days. To classify tweet content, we use a variant of latent Dirichlet allocation (LDA), an algorithm that has grown in popularity in the accounting literature and has been used in a number of studies (see, e.g., Dyer et al. 2017, Huang et al. 2018, Brown et al. 2020, Crowley et al. 2024). LDA is a machine-learning algorithm by Blei et al. (2003) that classifies the thematic content (i.e., topics) of text in a Bayesian manner without any oversight from the researcher. The key idea is that words that co-occur within documents tend to be related, and LDA uses this co-occurrence to construct weighted dictionaries to represent each topic. Unlike other methods in the literature, including classification models using bidirectional encoder representations from transformers (BERT) such as those of Huang et al. (2023) and Fritsch et al. (2025), LDA-based methods conduct unsupervised classification, determining the categories without needing any examples of them.⁶

The variant of LDA we use, the Twitter-LDA algorithm by Zhao et al. (2011), is a modified version of LDA that adjusts for the short length of tweets by leveraging word co-occurrence within users, as short “documents” are a noted problem for LDA. Based on manually optimizing the number of topics for interpretability, we obtain a set of 60 topics discussed across tweets in our data. Each topic is represented by a weighted dictionary from Twitter-LDA, and by using these weighted dictionaries, we can classify each tweet into one of the topics based on the topic with the highest weight. We manually label each topic based on the top 20 words in each topic, and then we cluster these 60 topics into three overarching categories of

information: *financial*, *nonfinancial business*, and *other*. Financial tweets are represented by one topic from the Twitter-LDA model and are likely to be the most informative tweets for investors, as financial information is crucial for evaluating firm performance and valuation. Examples of executive financial tweets include “In 3QFY17 @Sprint’s operating income more than doubled YoY and was positive for 8th consecutive quarter! [flexed biceps emoji] \$S [image]” and “\$LOGM announces 25% revenue growth and increases FY’15 revenue guidance in Q1 2015 results: [link].” Nonfinancial business tweets are company-relevant tweets covered by 42 topics such as business events, marketing, conference participation, and customer support; thus, they may be of interest to investors. Examples posted by executives include “Wrapping up @sat12 conference. A productive week for @IridiumComm and fun for me. Tired feet. Loved the @IridiumNEXT Mission Team launch!” and “And now I’m working on Board slides. Pretty excited about this week’s meeting.” Other tweets are likely unrelated to the firm and are covered by 17 topics about day-to-day life, sports, travel, and other interests. Examples of other executive tweets include “[username] I’d like to have the recipe” and “onto a day of errands after making myself a great breakfast.”⁷ Online Appendix OA.2 presents additional examples of tweets from each category. It also contains additional details on the construction of the topics, as well as examples of the most common words and bigrams from tweets in each category. For our analyses, we aggregate tweets by counting the number of tweets by each executive and firm in each category on each trading day or part thereof.

We validate the measure by manually coding 500 tweets from each of the three categories. We find an average agreement of 65% between manual coding and our algorithm. For financial tweets, we find 60.8% agreement, which is comparable to the accuracy in isolating financial tweets documented in Crowley et al. (2024). For nonfinancial business tweets, we find 70.2% agreement, and for other tweets, we find 65% agreement. Overall, our Twitter-LDA implementation performs well at classifying financial tweets. Online Appendix OA.3 provides more details on the validation exercise.

We provide summary statistics showing the number of tweets from each of the three tweet categories in Table 1, panel B. Across the 142,560 executive tweets in our sample, 78,123 discuss other matters not related to business, 63,298 discuss nonfinancial business matters, and 1,139 discuss financial matters. Taken together, executives frequently discuss both business and non-business matters, but discussing financial information is relatively rare.

To explore variation in the tweets executives and firms post, we classify the sentiment of these tweets. We use Valence Aware Dictionary and sEntiment

Reasoner (VADER; Hutto and Gilbert 2014), a tweet-specific sentiment measure. VADER is a widely used model for social media applications in computational social science and is used in accounting studies such as Shanthikumar et al. (2021), Abramova et al. (2024), Crowley et al. (2025), and Long et al. (2025).⁸ The method is designed to handle language as it is typically used on Twitter, including online slang and emojis. We apply VADER at the tweet level and classify each tweet as positive, negative, or neutral following the model's suggested weighting. We then aggregate the number of tweets by topic categories and sentiment, for example, the number of financial tweets that are positive on the trading day.⁹

For Twitter-based control variables, we include the log of one plus the number of followers of each account, the log of one plus the number of accounts the executive or firm Twitter account is following, and the log of one plus the total number of tweets posted by the account to date. Among our Twitter-derived control variables, followers and following are left-censored measures, as Twitter provides these measures at the time of access, not historically. Consequently, for the executives and firms on Twitter in our initial collection, we have time varying data throughout 2017 and 2018; for the accounts collected in our second collection exercise, we have these figures only as of July 1, 2021. We backfill these measures using the closest data we have for the account.

To test the mechanism through which executive tweets may impact the market, we introduce to the accounting literature a fine-grained measure of the content or meaning of sentence-length text: universal sentence encoder. The USE algorithm, developed by Cer et al. (2018) at Google, is a transformer neural network (the same technology underlying popular methods such as BERT) that processes sentences or short paragraphs, factoring in word order to represent the meaning of a sentence in a numeric form. The brevity of tweets allows us to directly encode whole tweets with USE. For our analysis, we use a model pretrained on a variety of online information sources, including "Wikipedia, web news, web question-answer pages and discussion forums" (Cer et al. 2018, p. 3). Given that Twitter is also a source of general web content, we expect this model to transfer well to our context. The USE algorithm maps each tweet to a vector that represents the meaning of the tweet. Tweets with similar meanings are mapped to similar vectors. We leverage this feature to precisely measure the similarity of executive tweets to firm tweets.

For example, consider the following tweets by Salesforce and CEO Marc Benioff on September 15, 2015. At 1:12 p.m., Salesforce tweeted "@Dreamforce powers Salesforce's market rise [salesforce link] (via @usatoday)." Two hours later, the CEO tweeted "Thanks [journalist's

username] 'Dreamforce powers Salesforce's market rise' #df15 [USA today link]." The content here is the same: both tweets highlight a news article that has positive implications for the firm. However, the framing is slightly different: the two tweets include different hyperlinks, and the CEO's tweet includes a callout to the journalist and a hashtag. This pair of tweets has a high similarity score under our measure. In contrast, on December 5, 2018, the same CEO retweeted his co-CEO Keith Block, thanking CNBC for having an interview on Salesforce's growth. Salesforce, however, had not sent any message about the interview, and thus the closest tweet was thanking Chicago's mayor for tweeting about a new Salesforce office in the city.¹⁰ This pair of tweets receives a very low similarity score. Online Appendix OA.4 provides additional examples of sentences encoded with this algorithm and their respective similarities, along with a more detailed description of our methodology.

For each executive financial tweet, we identify the set of all preceding tweets by the executive's firm in the two days (48 hours) leading up to the second before the executive tweet was posted. We then search the set of firm tweets for the tweet with the closest meaning to the executive financial tweet based on the representation of the tweets from USE.¹¹ We calculate the minimum distance for each tweet, normalize the distances to the interval [0, 1], and then convert the measure from a distance to a similarity (*Tweet similarity*) by taking one minus the normalized distance. We aggregate *Tweet similarity* by taking the mean across all financial tweets by the executive on the trading day. A higher *Tweet similarity* score indicates a financial tweet or set of financial tweets that is more consistent with the meaning of existing tweets by the executive's firm, whereas a lower score indicates financial tweets that differ in content from those of the executive's firm.¹²

2.2.2. Market Reaction Measures. Our primary return measures are based on market model return (MMR). We calculate betas using three months of lagged daily returns and S&P 500 returns. Our main tests focus on returns on the contemporaneous trading day t .¹³ Studies in accounting often use multiday windows of $[t - 1, t + 1]$ or $[t, t + 1]$ to account for information leakage or expectations of investors about scheduled events; however, as we are interested in the market reaction to the tweets by executives themselves, we focus only on day t . In an additional test, we examine market return following tweets that occurred from market close on day $t - 1$ up to market open on day t , which eliminates the concern of reverse causality from executives tweeting due to same-day stock price movements.

We also implement measures based on trading volume. We examine overall market volume changes, calculating *Abnormal volume* following Beaver et al. (2020). This measure is defined as the volume on day t

normalized by the volume on a control period of days $[t - 130, t - 10]$ and $[t + 10, t + 130]$, divided by the standard deviation of volume over the same control period. We also examine two measures of retail trading behavior, following Barber et al. (2024b) to identify retail trades and whether such trades are more likely to be buy or sell trades. Our first retail trading measure, *Abnormal retail trading*, follows from Blankespoor et al. (2019) and is calculated as the ratio of the percentage of trades attributed to retail trading on day t divided by the average daily percentage of trades attributed to retail trading over the window $[t - 41, t - 11]$.¹⁴ For consistency with our other market measures, we use only a single trading day in the numerator. Next, we examine retail buy–sell imbalance following Barber et al. (2024a). Retail buy–sell imbalance (*Retail BSI*) speaks to the direction of trading by retail investors. This serves as a signed measure in our trading volume tests, paralleling our signed return tests. For tests of retail buy–sell imbalance, we restrict the sample to firm-trading days with at least 10 retail trades as in Barber et al. (2024a). In cross-sectional analyses, we examine splits by *Retail trading*, which is the numerator of *Abnormal retail trading*.

3. Market Response Tests

3.1. Univariate Analysis

To understand how the presence of executives and firms changes over time during our sample period, in untabulated analyses, we examine the presence of S&P 1500 executives and firms on Twitter each year. At the start of our data in 2011, only 2.6% of executives (103 executives) are on Twitter. By 2018, 12.1% of executives (451 executives) are on Twitter, demonstrating substantial growth of the platform among executives. The aggregate market capitalization represented by firms with executives on Twitter has likewise increased, starting at 4.4% in 2011 up to 29% in 2018. Looking specifically at 2018, we see that some industries' executives are particularly likely to be on Twitter, such as those from communication services (23.7% of executives) and information technology (19.9% of executives), whereas the real estate industry is least represented, with only 5.6% of its executives on the platform. Figures showing yearly percentages of executives and firms on Twitter are presented in panels A and B of Online Appendix OA.5. In addition, Online Appendix OA.6 presents a determinants model of executives joining Twitter, examining executive, regulatory, and firm characteristics. We find that younger, female, and more extraverted executives are more likely to use Twitter, and that the 2013 SEC report is followed by an increase in executives joining the platform. The executives tend to work for smaller, less profitable firms and those with higher litigation risk.

Next, we examine how and when executives tweet, with corresponding figures presented in Online Appendix OA.5. There is a sustained increase in the number of executive tweets each year from 2011 through 2017, followed by a decrease in 2018. This decrease is likely attributable to the increased length of tweets starting from November 7, 2017, because longer messages could be posted in fewer tweets. We also examine the distribution of different topics of tweet content over the sample period. The distribution of executive tweet content is stable over time; slightly over half of tweets are on other topics, just under half of tweets are about nonfinancial business topics, and around 1% of tweets are on financial matters in each year. Relative to firms, executives have a higher proportion of financial tweets and a lower proportion of nonfinancial business tweets, and this difference is consistent throughout the sample period. In 2018, the distribution of executives' tweet content is 0.6% financial, 46.2% nonfinancial business, and 53.2% other.

Looking at when executives tweet, also presented in Online Appendix OA.5, we find that financial tweets make up a larger proportion of tweets on days when markets are open, especially between 6:00 a.m. and 9:00 a.m., though rates of posting financial tweets remain above average until 10:00 p.m. In contrast, executives rarely post financial tweets on weekends or holidays when financial markets are closed. Similarly, executives post nonfinancial business tweets more often on days when markets are open, and other tweets dominate after markets close for the day and on days off. Last, we examine the days and times when each type of tweet is most likely to occur. Executives tweet more on weekdays across all types of content, though other tweets are most evenly spread throughout the week. Financial tweets are posted much less on weekends, and they are posted most often around market open and close on Tuesdays, Wednesdays, and Thursdays. In Online Appendix OA.7, we present the univariate distribution of executives' tweets around earnings announcements and earnings calls. We see a pronounced increase in posting of financial tweets following earnings announcements and both before and after earnings calls. We also present multivariate analyses of executives tweeting around corporate events, showing that they tweet more around earnings events and 10-K, 10-Q, and 8-K filings compared with nonevent days. Both these results suggest that executives may tweet about matters that are relevant to investors' interests.

Table 2 presents univariate statistics for our main regression sample restricted to observations where both executives and their firms are on Twitter. Our regression sample consists of 376,445 executive-trading day observations, with executives posting an average of 0.38 tweets per day and their firms posting around 14.9 tweets per day. The relatively low number of

Table 2. Univariate Statistics, Daily Sample of Executives on Twitter

Variables	N	Mean	S.D.	p25	p50	p75
Trading day tweet measures						
<i>Financial tweets, Executive</i>	376,445	0.003	0.067	0	0	0
<i>Nonfin business tweets, Executive</i>	376,445	0.168	1.21	0	0	0
<i>Other tweets, Executive</i>	376,445	0.208	1.87	0	0	0
<i>Financial tweets, Firm</i>	376,445	0.045	0.286	0	0	0
<i>Nonfin business tweets, Firm</i>	376,445	7.45	88.4	0	1	4
<i>Other tweets, Firm</i>	376,445	7.39	127	0	1	3
Tweet sentiment measures						
<i>Financial, Nonnegative, Executive</i>	376,445	0.003	0.062	0	0	0
<i>Financial, Negative, Executive</i>	376,445	0.000	0.019	0	0	0
<i>Nonfin business, Nonnegative, Executive</i>	376,445	0.150	1.07	0	0	0
<i>Nonfin business, Negative, Executive</i>	376,445	0.018	0.216	0	0	0
<i>Other, Nonnegative, Executive</i>	376,445	0.190	1.74	0	0	0
<i>Other, Negative, Executive</i>	376,445	0.018	0.229	0	0	0
<i>Financial tweets, Nonnegative, Firm</i>	376,445	0.040	0.265	0	0	0
<i>Financial tweets, Negative, Firm</i>	376,445	0.005	0.083	0	0	0
<i>Nonfin business, Nonnegative, Firm</i>	376,445	6.69	76.5	0	1	4
<i>Nonfin business, Negative, Firm</i>	376,445	0.759	29.7	0	0	0
<i>Other, Nonnegative, Firm</i>	376,445	6.89	126	0	1	3
<i>Other, Negative, Firm</i>	376,445	0.500	3.46	0	0	0
Tweets' timing measures						
During trading day						
<i>Financial tweets, Executive</i>	376,445	0.001	0.036	0	0	0
<i>Nonfin business tweets, Executive</i>	376,445	0.060	0.488	0	0	0
<i>Other tweets, Executive</i>	376,445	0.064	0.597	0	0	0
<i>Financial tweets, Firm</i>	376,445	0.022	0.173	0	0	0
<i>Nonfin business tweets, Firm</i>	376,445	3.06	31.1	0	0	2
<i>Other tweets, Firm</i>	376,445	2.82	25.8	0	0	2
Before trading day						
<i>Financial tweets, Executive</i>	376,445	0.002	0.053	0	0	0
<i>Nonfin business tweets, Executive</i>	376,445	0.108	0.916	0	0	0
<i>Other tweets, Executive</i>	376,445	0.144	1.48	0	0	0
<i>Financial tweets, Firm</i>	376,445	0.023	0.198	0	0	0
<i>Nonfin business tweets, Firm</i>	376,445	4.39	76.1	0	0	2
<i>Other tweets, Firm</i>	376,445	4.58	113	0	0	1
Mechanism test measures						
<i>Tweet similarity</i>	288,143	0.001	0.023	0	0	0
<i>Matched financial tweets, Executive</i>	376,445	0.003	0.062	0	0	0
<i>Unmatched financial tweets, Executive</i>	376,445	0.001	0.023	0	0	0
Dependent variables						
$ MMR_t $	376,445	0.013	0.017	0.004	0.008	0.016
MMR_t	376,445	0.000	0.022	−0.008	−0.000	0.008
<i>Abnormal volume</i>	376,277	0.041	1.34	−0.542	−0.235	0.238
<i>Abnormal retail trading</i>	367,995	1.02	0.485	0.745	0.950	1.20
<i>Retail BSI</i>	345,225	−0.017	0.239	−0.149	−0.008	0.120
Control variables						
<i>Executive age</i>	376,445	52.6	6.81	48	52	57
<i>Size</i>	376,445	7.85	1.87	6.41	7.59	9.11
<i>ROA</i>	376,445	0.009	0.032	0.002	0.011	0.022
<i>MTB</i>	376,445	1.85	1.93	0.640	1.16	2.39
<i>Debt</i>	376,445	0.556	0.254	0.380	0.551	0.713
<i>Firm event</i>	376,445	0.446	0.497	0	0	1
<i>log(Followers, Executive)</i>	376,445	3.37	3.85	0	2.08	6.43
<i>log(Following, Executive)</i>	376,445	2.57	2.66	0	2.20	5.06
<i>log(Total tweets, Executive)</i>	376,445	0.576	1.86	0	0	0
<i>log(Followers, Firm)</i>	376,445	8.86	3.39	7.30	8.94	10.8
<i>log(Following, Firm)</i>	376,445	6.23	2.37	5.16	6.50	7.66
<i>log(Total tweets, Firm)</i>	376,445	7.26	2.79	6.05	7.91	9.10

Notes. This table presents univariate statistics for all independent variables, dependent variables, and control variables. Discrepancies between firm tweets counts in Tables 1 and 2 are due to duplication of firm data when a firm's CEO and CFO are both on Twitter. S.D., Standard deviation.

tweets per executive per day is in part due to 179 executives who had Twitter accounts but never tweeted during 2012–2018 or, if they did, only did so before their firm joined Twitter. We keep these executives for our tests, as these executives *could* release a public tweet at any time. The average executive has 70,877 followers and is following 181 accounts (untabulated).

3.2. Market Response to Executive Financial Tweets

We examine market response around executive tweets. We first model unsigned and signed market model returns. We include unsigned market model return, as this measure can capture stock market reaction to disclosures with no ex ante known directional impact (e.g., Campbell et al. 2014, Hope et al. 2016). We also examine market volume proxied by *Abnormal volume*, *Abnormal retail trading*, and *Retail BSI*. We conduct our market tests using linear regression with high-dimensional fixed effects (HDFEs) and standard errors clustered by executive and trading day:

$$\begin{aligned} DV_{t,e,f} &= \alpha + \beta_1 \text{Financial tweets, Executive}_{t,e} \\ &+ \beta_2 \text{Nonfin business tweets, Executive}_{t,e} \\ &+ \beta_3 \text{Other tweets, Executive}_{t,e} + \beta_4 \text{Financial tweets, Firm}_{t,f} \\ &+ \beta_5 \text{Nonfin business tweets, Firm}_{t,f} + \beta_6 \text{Other tweets, Firm}_{t,f} \\ &+ \beta_7 \text{Return}_{t-1,f} + \beta_8 \text{Executive age}_{t,e} + \beta_{(9-13)} \cdot \text{Firm controls}_{t,f} \\ &+ \beta_{(14-19)} \cdot \text{Twitter controls}_{t,e,f} + FE(\text{Firm, Exec, Year, Month}) \\ &+ \varepsilon_{t,e,f}. \end{aligned} \quad (1)$$

In our initial test, our independent variables of interest are the executive tweet measures split on content type. We control for firms' tweets to disentangle the effect of firm social media activity from the effect of executive tweets. In all tests, we control for unsigned or signed market model returns on day $t - 1$ ($\text{Return}_{t-1,f}$), executive age (*Age*), firm size (*Size*), return on assets (*ROA*), market to book ratio (*MTB*), debt to assets ratio (*Debt*), firm events (*Firm event*), and Twitter account characteristics. *Firm event* captures the presence of any earnings conference call or earnings announcement, as well as the release of a 10-K, 10-Q, or 8-K filing. For both executive and firm Twitter accounts, we control for the number of followers the account has, the total tweets previously posted by the account, and the number of accounts it follows. Appendix B lists the definitions of all variables. Last, we include a comprehensive collection of fixed effects: firm, executive (which differentiates between CEO and CFO within firm), and year and month to capture any linear time trends in tweeting behavior.

Table 3 presents regression results for our market tests. For unsigned return (column (1)), we find

differing results across executive tweet types. We do not find any evidence that nonfinancial business tweets affect market return, and we find that other tweets are associated with a statistically significant but economically small decrease in market reaction. In contrast, executive financial tweets are associated with a higher magnitude of market reaction, at 0.4% per financial tweet. Comparing executives' financial tweets to those of their firms, we find that financial tweets by executives are associated with 2.8 times the reaction per tweet of firms' financial tweets; this difference is significant ($p < 0.01$). This indicates that executive financial tweets may be more important than firm financial tweets when they occur. In terms of economic significance, executives' financial tweets account for 17% of the total stock market movement associated with financial tweets by both executives and firms.¹⁵

Column (2) presents the regression result using signed return. Here we see no effect of nonfinancial and other tweets posted by executives, yet we find that executive financial tweets are followed by positive stock returns. The effect is economically meaningful at a 0.2% increase in stock price per financial tweet, on average. This result is consistent with executives having an incentive to use social media to raise their firm's stock price. In contrast, we see no significant market reaction to firm financial and nonfinancial tweets, and we find a negative and significant association of other tweets, though the effect is economically small. When we compare executives' financial tweets with their firms' financial tweets, we find that executive financial tweets have approximately 10 times the impact, on average, and the difference between the coefficients is statistically significant ($p < 0.10$) in the full specification. Overall, these results are consistent with the market only reacting to executive financial tweets, with limited signed return impact of all other types of tweets by executives.

In columns (3) through (5), we examine the effect of executive tweets on trading volume. First, in column (3), we examine the level of abnormal volume in response to executive tweets. We again find no effect of most executive tweets, but we do find a large increase in volume following executive financial tweets. We also see a positive and statistically significant impact of firm financial tweets, though with a smaller effect size than that of executive financial tweets. The effect size of executive financial tweets is around 2.4 times that of firm financial tweets, and the difference is statistically significant ($p < 0.01$). Taken together, these two results are consistent with financial tweets driving investors to trade more. Next, we examine retail trading behavior, as we expect social media content to influence retail investors. Column (4) presents results for abnormal retail trading. It shows that retail traders appear to trade more when executives post financial tweets, with

Table 3. Market Response to Executive Tweets

Variables	$ MMR_t $ (1)	MMR_t (2)	<i>Abnormal</i> <i>volume</i> _{<i>t</i>} (3)	<i>Abnormal</i> <i>retail trading</i> _{<i>t</i>} (4)	<i>Retail</i> <i>BSI</i> _{<i>t</i>} (5)
Executive tweets					
<i>Financial tweets</i>	0.004*** (4.65)	0.002* (1.88)	0.416*** (4.77)	0.031** (2.20)	0.012** (1.99)
<i>Nonfin business tweets</i>	0.000 (1.00)	−0.000 (−0.96)	−0.002 (−0.84)	0.002 (1.29)	0.001 (1.31)
<i>Other tweets</i>	−0.000*** (−4.19)	−0.000 (−0.38)	0.000 (0.41)	−0.000 (−0.30)	−0.001* (−1.70)
Firm tweets					
<i>Financial tweets</i>	0.002*** (4.49)	0.000 (1.08)	0.176*** (5.96)	0.000 (0.12)	0.001 (0.70)
<i>Nonfin business tweets</i>	0.000 (1.05)	0.000 (0.73)	0.000 (1.12)	0.000 (0.83)	0.000 (0.78)
<i>Other tweets</i>	−0.000*** (−3.69)	−0.000* (−1.84)	−0.000** (−2.38)	−0.000 (−1.22)	−0.000 (−0.73)
$ MMR_{t-1} $	0.129*** (15.83)		16.092*** (12.03)	2.006*** (15.61)	
MMR_{t-1}		−0.003 (−0.42)			0.402*** (13.54)
<i>Executive age</i>	0.000 (1.24)	0.000 (0.80)	−0.006 (−0.30)	0.008 (0.86)	0.003 (1.04)
<i>Size</i>	−0.001* (−1.81)	−0.000 (−0.40)	0.007 (0.42)	0.001 (0.13)	0.018** (2.47)
<i>ROA</i>	−0.002 (−0.53)	0.005 (1.46)	0.015 (0.08)	−0.194* (−1.83)	0.093* (1.73)
<i>MTB</i>	−0.000** (−2.52)	0.001*** (7.57)	−0.010** (−2.51)	0.004* (1.68)	0.012*** (7.51)
<i>Debt</i>	0.005*** (2.80)	0.000 (0.58)	−0.142** (−2.35)	−0.020 (−0.76)	−0.004 (−0.24)
<i>Firm event</i>	0.004*** (22.97)	0.000*** (2.94)	0.308*** (30.21)	0.027*** (9.11)	0.005*** (4.59)
<i>log(Followers, Firm)</i>	−0.000 (−0.19)	0.000 (1.42)	−0.003 (−0.46)	0.003 (1.30)	−0.002 (−0.78)
<i>log(Following, Firm)</i>	−0.000 (−0.70)	−0.000 (−0.49)	0.009 (1.36)	−0.002 (−0.54)	−0.001 (−0.25)
<i>log(Total tweets, Firm)</i>	0.000 (0.65)	−0.000 (−0.64)	−0.004 (−0.78)	−0.005* (−1.66)	0.000 (0.12)
<i>log(Followers, Executive)</i>	−0.000*** (−3.06)	−0.000 (−0.98)	−0.001 (−0.31)	−0.005*** (−3.72)	0.002 (0.81)
<i>log(Following, Executive)</i>	0.000** (2.40)	0.000 (0.52)	0.003 (0.52)	0.006** (2.30)	−0.002 (−0.61)
<i>log(Total tweets, Executive)</i>	0.000 (0.78)	0.000*** (3.00)	−0.001 (−0.60)	−0.001 (−1.28)	−0.000 (−0.60)
Firm, executive, year, and month FEs	Yes	Yes	Yes	Yes	Yes
Exec – firm fin tweets, <i>F</i> -test	7.80***	2.75*	6.87***	4.32**	3.17*
Adjusted R^2	0.119	0.001	0.057	0.014	0.041
Observations	376,445	376,445	376,277	367,995	345,225

Notes. This table presents the results of regression Equation (1), run on the main regression sample using linear regression. The dependent variables are unsigned market model return on day t in column (1), signed market model return on day t in column (2), abnormal volume following Beaver et al. (2020) in column (3), abnormal retail trading following Blankespoor et al. (2019) in column (4), and retail buy–sell imbalance following Barber et al. (2024a) in column (5). Retail trades are classified based on the Barber et al. (2024b) method. Column (5) is restricted to firm-trading days with at least 10 retail trades. The “Exec – firm” row documents *F*-test statistics between the coefficients on executive and firm financial (fin) tweets. All standard errors are clustered by executive and trading day. The t statistics are presented in parentheses.

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

the amount of retail trades increasing by approximately 3.0% per financial tweet as compared with the average level of retail trading. However, we find no effect of executives’ nonfinancial business and

other tweets. We also see no evidence that firm tweets affect retail trading. Last, we examine retail buy–sell imbalance in column (5). Consistent with executive financial tweets increasing stock prices as shown in

column (2), we find that retail traders place additional buy trades as compared with sell trades following executive financial tweets. Holding retail sell trades constant, the coefficient of 0.012 on executive financial tweets is equivalent to an increase in retail buy trades of 0.6% per tweet. We find no effect of executive nonfinancial business tweets, and we find an opposite effect of other tweets posted by executives, though the effect size is small.

Taken together, these results suggest that most executive tweets have a minimal effect on the market. Executive nonfinancial business tweets appear to have no effect on any of our examined market outcomes, and other tweets have a limited impact on the market. In contrast, executive financial tweets are followed by stock price changes and additional trading in the market, with part of this trading possibly driven by retail traders. In addition, retail traders appear to be placing more buy trades than sell trades in conjunction with executive financial tweets.

3.3. Market Response and Characteristics of Executive Financial Tweets

To better understand how executive financial tweets are associated with directional market outcomes, we examine how market response varies with the sentiment and posting time of executive tweets. First, we split our tweet measures based on the sentiment of the tweets. We find that 51% of executive tweets are positive, 39% are neutral, and 10% are negative. Looking only at executive financial tweets, 59% are positive, 30% are neutral, and 11% are negative. The imbalance between positive and negative tweets may explain why the number of executive financial tweets posted is positively associated with signed return and retail buy–sell imbalance. Firm tweets show a similarly imbalanced distribution, with 64% being positive, 28% being neutral, and 8% being negative, whereas for firm financial tweets, 50% are positive, 39% are neutral, and 11% are negative.

To examine the impact of sentiment, we separate out negative tweets and nonnegative (positive or neutral) tweets within each category of tweet content; we combine positive and neutral content as the Pearson correlation between posting positive and neutral tweets is 80% for executives. We then adjust regression Equation (1) to split the daily executive and firm tweet count measures into the counts of nonnegative and negative tweets from their respective categories. Table 4 shows the results, documenting the relationship between tweet sentiment and directional outcomes. Column (1) examines how signed market return is affected. For executives, we find a significant effect only of nonnegative executive financial tweets, and, consistent with our results in Table 3, these tweets drive a positive market reaction. Furthermore, the coefficient is very similar in

Table 4. Market Response to Executive Tweets

Variables	MMR _t (1)	Retail BSI _t (2)
Executive tweets		
Financial tweets, Nonnegative	0.002* (1.87)	0.013** (2.18)
Financial tweets, Negative	−0.001 (−0.23)	0.002 (0.09)
Nonfin business tweets, Nonnegative	−0.000 (−0.48)	0.001 (0.87)
Nonfin business tweets, Negative	−0.000 (−0.62)	0.001 (0.51)
Other tweets, Nonnegative	−0.000 (−0.38)	−0.001 (−1.55)
Other tweets, Negative	0.000 (0.10)	−0.002 (−0.90)
Firm tweets		
Financial tweets, Nonnegative	0.000 (1.44)	0.000 (0.26)
Financial tweets, Negative	−0.001* (−1.80)	0.004 (0.60)
Nonfin business tweets, Nonnegative	0.000 (0.79)	0.000 (0.56)
Nonfin business tweets, Negative	0.000 (0.07)	−0.000 (−1.04)
Other tweets, Nonnegative	−0.000* (−1.68)	−0.000 (−1.19)
Other tweets, Negative	−0.000 (−0.84)	0.000 (1.32)
All controls	Yes	Yes
Firm, executive, year, and month FEs	Yes	Yes
Exec nonnegative – negative fin tweets, F-test	0.96	0.34
Exec – firm nonnegative fin tweets, F-test	2.53	4.08**
Adjusted R ²	0.001	0.041
Observations	376,445	345,225

Notes. This table presents the results of regression Equation (1) when splitting tweet measures on the sentiment of the tweets, run on the main regression sample using linear regression. The dependent variables are signed market model return on day t in column (1) and retail buy–sell imbalance following Barber et al. (2024a) in column (2). Retail trades are classified based on the Barber et al. (2024b) method. Column (2) is restricted to firm-trading days with at least 10 retail trades. The “Exec nonnegative – negative” and “Exec – firm nonnegative” rows document F -test statistics between the coefficients on executive nonnegative and negative financial (fin) tweets and executive and firm nonnegative financial (fin) tweets, respectively. All controls from Appendix B are included. All standard errors are clustered by executive and trading day. The t statistics are presented in parentheses.

** $p < 0.05$; * $p < 0.1$.

magnitude to the result in Table 3. In contrast, we do not see any negative market effect of negative financial tweets by executives, and the difference between the nonnegative and negative financial tweet coefficients is insignificant. This may be due to the relative infrequency of negative financial tweets, as they represent only 11% of executive financial tweets. For firms, however, we do see a statistically significant and negative effect of posting negative financial tweets. Table 4, column (2), examines the effect of executive tweet

sentiment on retail buy–sell imbalance. For executives, we again find that only nonnegative financial tweets are associated with a positive and statistically significant effect, and the effect size is comparable to our result in Table 3.

Next, we examine how market reaction is associated with executive financial tweets in relation to when the tweets were posted. To examine reaction around intraday patterns of executive tweeting, we split each trading day into two time periods: *before trading* and *during trading*. If the tweet occurs after the closing time on trading day $t - 1$ and before the opening time on trading day t , we assign it to the *before trading* period of day t . If the tweet occurs on trading day t and is released

between the open and the close of the stock market (9:30 a.m. to 4:00 p.m. in the eastern time zone), we assign it to the *during trading* period for day t . A timeline of these periods is included in Online Appendix OA.1. For tweets posted before the trading period, investors must wait until the market opens to trade. Examining these tweets thus helps to lessen the endogeneity concern that executives, through their tweets, are simply responding to changes in the day's stock price. In contrast, although examining tweets posted during the day allows us to examine a timely response to executive financial tweets, it is difficult to rule out the possibility that executives tweet in response to changes in stock price in our specification.

Table 5. Market Response Partitioned on Timing of Executive Tweets

Variables	$ MMR_t $ (1)	MMR_t (2)	<i>Abnormal</i> <i>volume</i> _{t} (3)	<i>Abnormal</i> <i>retail trading</i> _{t} (4)	<i>Retail</i> <i>BSI</i> _{t} (5)
Executive tweets					
<i>Financial tweets, before trading</i>	0.004*** (3.98)	0.001 (1.00)	0.492*** (5.09)	0.037** (2.14)	0.011* (1.81)
<i>Nonfin business tweets, before trading</i>	0.000 (1.32)	0.000 (0.14)	−0.002 (−0.57)	0.003* (1.85)	0.001 (0.95)
<i>Other tweets, before trading</i>	−0.000*** (−3.52)	−0.000* (−1.68)	−0.001 (−0.73)	0.000 (0.16)	−0.001* (−1.84)
<i>Financial tweets, during trading</i>	0.004** (2.56)	0.003** (2.15)	0.258*** (2.71)	0.018 (0.90)	0.013 (1.50)
<i>Nonfin business tweets, during trading</i>	−0.000 (−0.28)	−0.000 (−1.41)	−0.002 (−0.22)	−0.001 (−0.35)	0.001 (1.15)
<i>Other tweets, during trading</i>	−0.000 (−1.01)	0.000 (1.38)	0.007* (1.75)	−0.003* (−1.89)	−0.000 (−0.08)
Firm tweets					
<i>Financial tweets, before trading</i>	0.003*** (4.65)	0.000 (1.26)	0.265*** (6.17)	0.007 (1.17)	0.002 (1.38)
<i>Nonfin business tweets, before trading</i>	0.000 (1.27)	0.000 (0.96)	0.000 (1.55)	0.000 (0.53)	0.000 (0.91)
<i>Other tweets, before trading</i>	−0.000* (−1.94)	−0.000 (−0.92)	−0.000** (−2.28)	0.000 (0.08)	−0.000 (−1.05)
<i>Financial tweets, during trading</i>	0.000 (0.98)	−0.000 (−0.29)	0.062*** (2.61)	−0.008* (−1.88)	−0.001 (−0.37)
<i>Nonfin business tweets, during trading</i>	−0.000 (−0.65)	−0.000 (−0.44)	−0.000 (−1.37)	0.000 (1.29)	0.000 (0.47)
<i>Other tweets, during trading</i>	−0.000 (−0.77)	−0.000 (−1.56)	−0.000 (−1.64)	−0.000 (−1.22)	0.000 (0.59)
All controls	Yes	Yes	Yes	Yes	Yes
Firm, executive, year, and month FEs	Yes	Yes	Yes	Yes	Yes
Exec – firm fin tweets, before, <i>F</i> -test	2.23	0.47	4.69**	2.78*	1.92
Exec – firm fin tweets, during, <i>F</i> -test	5.80**	4.67**	3.93**	1.55	2.30
Adjusted R^2	0.119	0.001	0.057	0.014	0.041
Observations	376,445	376,445	376,277	367,995	345,225

Notes. This table presents the results of regression Equation (1) when splitting tweet measures on the time of day of the tweets, run on the main regression sample using linear regression. The dependent variables are unsigned market model return on day t in column (1), signed market model return on day t in column (2), abnormal volume following Beaver et al. (2020) in column (3), abnormal retail trading following Blankespoor et al. (2019) in column (4), and retail buy–sell imbalance following Barber et al. (2024a) in column (5). Retail trades are classified based on the Barber et al. (2024b) method. Column (5) is restricted to firm-trading days with at least 10 retail trades. The “Exec – firm” rows document *F*-test statistics between the coefficients on executive and firm financial (fin) tweets. All controls from Appendix B are included. All standard errors are clustered by executive and trading day. The t statistics are presented in parentheses.

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

Table 5 tests Equation (1) when the daily executive and firm tweet measures are split by the time of the tweets (during trading or before trading), using the same dependent variables as in Table 3. Across executive tweets posted before trading, we continue to see minimal impact on the market across most tweets. For nonfinancial business tweets, the only statistically significant result is a small increase in abnormal retail trading. For other tweets, we see a small drop in absolute abnormal return and retail buy–sell imbalance consistent with Table 3, and we also see a significant but small drop in signed abnormal return. In contrast, executive financial tweets posted before trading are associated with significant increases in unsigned abnormal return, abnormal volume, abnormal retail trading, and retail buy–sell imbalance. This result helps to rule out potential reverse causality of executives posting in response to market activity during the same trading day as the tweet, as the result is consistent with executives' posts before the market opens influencing trading behavior after the market opens. Turning to executive tweets posted during the trading day, we see no statistically significant impact of nonfinancial business tweets, and we find significant but small impacts of other tweets on abnormal volume and abnormal retail trading. Executive financial tweets, however, are associated with modest increases in unsigned and signed abnormal returns as well as abnormal volume. We do not see any impact on retail trading, possibly because of retail traders being slower to respond to the available information. This notion is consistent with the effects shown for executive tweets posted before trading, as retail traders have a longer time to react to those tweets. Taken together, the results suggest that executive financial tweets posted both before and during trading hours are followed by an increase in stock market reaction, and that the directional increase in stock returns is associated with tweets posted during the trading session.

4. Mechanism: Market Response to Financial Tweets

4.1. Market Response Mechanism Tests

To examine the mechanism underlying the market response to executive financial tweets, we use the same regression structure as in our market tests, with some adjustments. To examine the new information mechanism, we split the *Financial tweets, Executive* measure into two measures based on whether the executive's financial tweet is preceded by any tweet from their firm in the prior 48 hours.¹⁶ If the firm posted any tweet in the prior 48 hours, we classify the executive financial tweet as a matched financial tweet. For these tweets, it is more likely that the tweet's information was already

posted on Twitter by the firm. In contrast, if the firm did not post a tweet in the prior 48 hours, then we classify the executive financial tweet as an unmatched financial tweet, and these tweets are more likely to contain new information. Of the 968 executive-trading day observations with financial tweets, 804 contain matched tweets and 164 only contain unmatched tweets. For our mechanism tests, we retain the same dependent variables from our market behavior tests. The full model is implemented using a linear regression with HDFEs and clustered standard errors (by executive and trading day). The equation, with the same controls and fixed effects as in Equation (1), is as follows:

$$\begin{aligned}
 DV_{t,e,f} &= \alpha + \beta_1 \text{Unmatched financial tweets, Executive}_{t,e} \\
 &+ \beta_2 \text{Matched financial tweets, Executive}_{t,e} \\
 &+ \beta_3 \text{Nonfin business tweets, Executive}_{t,e} \\
 &+ \beta_4 \text{Other tweets, Executive}_{t,e} + \beta_5 \text{Financial tweets, Firm}_{t,f} \\
 &+ \beta_6 \text{Nonfin business tweets, Firm}_{t,f} + \beta_7 \text{Other tweets, Firm}_{t,f} \\
 &+ \beta_8 \text{Return}_{t-1,f} + \beta_9 \text{Executive age}_{t,e} + \beta_{10-14} \cdot \text{Firm controls}_{t,f} \\
 &+ \beta_{15-20} \cdot \text{Twitter controls}_{t,e,f} + FE(\text{Firm, Exec, Year, Month}) \\
 &+ \varepsilon_{t,e,f}.
 \end{aligned} \tag{2}$$

For each dependent variable, a positive value for β_1 is consistent with the new information mechanism. For the new information mechanism, we expect to find stronger results using unsigned return as compared with signed return, as new information could push the stock price in either direction depending on how it is perceived by the market. We do not have a clear expectation for trading volume–based measures. A positive value for β_2 is consistent with either the new information mechanism or the perceived credibility mechanism, which we will explore next.

To examine the perceived credibility mechanism, we restrict the sample to only those executive-trading day observations where the firm has tweeted during the day or the prior two days, as our *Tweet similarity* measure cannot be defined unless there is at least one firm tweet available to compute similarity. This results in a sample of 288,143 observations. Of these observations, only 804 days have nonzero *Tweet Similarity*, with a mean of 0.425 on these days. To test the mechanism, we fully interact *Financial tweets, Executive* with *Tweet similarity* and add the measures to Equation (1).¹⁷ The interaction term is our measure of interest, as it represents the incremental market impact of higher similarity between executive and firm tweets. We use the same dependent variables as for the new information mechanism test and implement the model using linear regression with HDFEs and clustered standard errors (by executive and trading day). The full model, where

controls and fixed effects are the same as for Equation (1), is as follows:

$$\begin{aligned}
 DV_{t,e,f} = & \alpha + \beta_1 \text{Financial tweets, Executive}_{t,e} \times \text{Tweet similarity}_{t,e,f} \\
 & + \beta_2 \text{Financial tweets, Executive}_{t,e} + \beta_3 \text{Financial tweets, Firm}_{t,f} \\
 & + \beta_4 \text{Tweet similarity}_{t,e,f} + \beta_5 \text{Nonfin business tweets, Executive}_{t,e} \\
 & + \beta_6 \text{Nonfin business tweets, Firm}_{t,f} + \beta_7 \text{Other tweets, Executive}_{t,e} \\
 & + \beta_8 \text{Other tweets, Firm}_{t,f} + \beta_9 \text{Return}_{t-1,f} + \beta_{10} \text{Executive age}_{t,e} \\
 & + \beta_{\{11-15\}} \cdot \text{Firm controls}_{t,f} + \beta_{\{16-21\}} \cdot \text{Twitter controls}_{t,e,f} \\
 & + FE(\text{Firm, Exec, Year, Month}) + \varepsilon_{t,e,f}.
 \end{aligned} \quad (3)$$

A positive and significant coefficient on the interaction term would suggest that the market responds more when executives post tweets that are more similar in content to those of their firm, supporting the perceived credibility mechanism. Alternatively, a negative and significant coefficient on the interaction term would indicate that investors react more strongly when executives post financial tweets that differ more from what

their firm has posted, which would be consistent with the new information mechanism. We expect stronger results for signed return, because perceived credibility can be leveraged by executives to garner a more favorable reaction. We do not have a clear expectation for trading volume-based measures.

Table 6 presents the results for our mechanism tests. Panel A shows our test for the new information mechanism following regression Equation (2). The new information mechanism is supported by any effect of unmatched financial tweets posted by executives, as these tweets are the most likely to contain new information. We find a statistically significant increase in unsigned market return to unmatched financial tweets, consistent with new information leading to market reaction. We also find a statistically significant increase in retail buy–sell imbalance, though we find no significant result for the other dependent variables. Therefore, we document some evidence in support of the market reacting to tweets because of the presence of new information. Looking at the matched financial

Table 6. Market Response Mechanisms

Variables	$ MMR_t $ (1)	MMR_t (2)	Abnormal volume _t (3)	Abnormal retail trading _t (4)	Retail BSI _t (5)
Panel A: New information mechanism					
Unmatched financial tweets, Executive	0.003* (1.86)	0.001 (0.61)	0.139 (1.54)	0.005 (0.14)	0.029** (2.28)
Matched financial tweets, Executive	0.004*** (4.72)	0.002* (1.84)	0.451*** (5.17)	0.037** (2.58)	0.010* (1.77)
Financial tweets, Firm	0.002*** (4.50)	0.000 (1.08)	0.176*** (5.97)	0.001 (0.14)	0.001 (0.71)
All controls	Yes	Yes	Yes	Yes	Yes
Firm, executive, year, and month Fes	Yes	Yes	Yes	Yes	Yes
Adjusted R ²	0.119	0.001	0.057	0.014	0.041
Observations	376,445	376,445	376,277	367,995	345,225
Panel B: Perceived credibility mechanism					
Financial tweets, Executive × Tweet similarity	0.012* (1.90)	0.021** (2.56)	2.20*** (5.55)	−0.102 (−0.71)	−0.033 (−0.70)
Financial tweets, Executive	0.002 (1.12)	−0.003 (−1.34)	−0.056 (−0.34)	0.134*** (2.84)	0.019 (1.00)
Financial tweets, Firm	0.002*** (4.64)	0.000 (0.99)	0.177*** (5.99)	0.001 (0.25)	0.001 (0.84)
Tweet similarity	−0.010** (−2.17)	−0.011* (−1.76)	−1.53*** (−5.95)	−0.201** (−2.58)	0.019 (0.75)
All controls	Yes	Yes	Yes	Yes	Yes
Firm, executive, year, and month FEs	Yes	Yes	Yes	Yes	Yes
Adjusted R ²	0.112	0.001	0.061	0.016	0.046
Observations	288,143	288,143	287,987	281,706	267,045

Notes. This table presents the results of regression Equations (2) and (3) in panels A and B, respectively. Panel A is estimated based on the main regression sample, whereas panel B is estimated based on a sample of all observations with at least one firm tweet in the preceding 48 hours. The dependent variables are unsigned market model return on day t in column (1), signed market model return on day t in column (2), abnormal volume following Beaver et al. (2020) in column (3), abnormal retail trading following Blankespoor et al. (2019) in column (4), and retail buy–sell imbalance following Barber et al. (2024a) in column (5). Retail trades are classified based on the Barber et al. (2024b) method. Column (5) is restricted to firm-trading days with at least 10 retail trades. All controls from Appendix B are included. All standard errors are clustered by executive and trading day. The t statistics are presented in parentheses.

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

tweets, we see a positive and significant association with all five dependent variables, which provides initial evidence that executive tweets either contain new information content or provide incremental credibility to the information in firm tweets.

In panel B, we present our test for the perceived credibility mechanism following regression Equation (3). Columns (1) and (2) present results for unsigned and signed market returns, respectively. We find a positive and significant coefficient on the interaction between executive financial tweets and *Tweet similarity* for both outcomes. This suggests that executive financial tweets that are more similar to existing tweets by the executive's firm receive greater reaction by the market, consistent with the perceived credibility mechanism. In addition, in column (3), we find a positive relationship between the interaction term and abnormal volume. However, we do not find any significant effects on retail trading measures. Overall, our results are consistent with the stock market reacting more strongly to executive financial tweets that are less likely to convey new information.

Taken together, our results indicate that both mechanisms, perceived credibility and new information, can play a role in how investors react to executive financial tweets. There are firm tweets to construct the *Tweet similarity* measure for approximately 83% of the observations with executive financial tweets, and the remaining 17% of observations are unmatched. Thus, our coefficients representing both mechanisms occur frequently enough to be economically meaningful. When a firm is active on Twitter, its executives' financial tweets can lead investors to perceive existing information from their firm's tweets as more credible. When a firm has not tweeted in the prior 48 hours, the executive can serve an information-providing role. Executives can fill the void left by their firms if their firms are not on Twitter.

4.2. Cross-Sectional Tests

To provide additional evidence on the perceived credibility and new information mechanisms, we conduct cross-sectional tests partitioning on three characteristics across which the mechanisms' effectiveness should vary. First, we partition on firm size, as larger firms are likely to be subject to greater attention from investors. These firms' executives are therefore likely to attract more attention on Twitter, which would lead to a greater impact via both mechanisms. Next, we partition on contemporaneous levels of retail trading. To the extent that retail traders are more likely to be the source of reaction to posts on Twitter, we would expect to find stronger mechanism results for firms that receive more attention from retail investors. Last, we partition on executives' follower count. Posts by executives with more followers should receive more attention, as their

tweets should have greater reach, leading to a greater impact of both mechanisms.

Firm size and retail trading are based on median splits among the observations with executives on Twitter. Retail trading is the numerator of *Abnormal retail trading*, defined as the average daily percentage of trades by retail investors on day t . For executives' follower count, we split on whether the executive is in the top decile, as executives' follower counts are highly skewed (median of two followers, 90th percentile of 4,722 followers). As we present cross-sections based on retail trading, we do not present cross-sectional results for our retail trading measures.

For the new information mechanism, we present the results in Table 7, panels A and B, using unsigned return and abnormal volume as the dependent variables, respectively. We focus on these two, as signed return shows little impact for this mechanism. We follow Equation (2), using the same controls, fixed effects, and clustering as in Table 6. In panel A, we find significant results on unmatched tweets only for firms with high levels of retail trading, and the difference is statistically significant compared with firms with low levels of retail trading. This is consistent with attention driving the effect of new information in executive tweets, though the lack of significance on the other two cross-sections suggests that the role of attention may be limited for the new information mechanism. For matched tweets we see statistically significant coefficients with larger magnitudes for high-attention firms and executives as compared with low-attention ones. However, the difference is only statistically significant for the partition on executive follower counts. Examining abnormal volume in panel B, we find statistically significant effects with larger coefficients for firms with high retail trading and executives with higher follower counts, though the differences across coefficients are insignificant. Again, this provides weak evidence that attention drives the reaction to new information. For matched tweets, we again see consistent results across all three splits, with significant differences across coefficients for all three partitions. Taken together, we find some evidence of attention driving reaction to new information.

We present results for the perceived credibility mechanism in Table 7, panels C and D, taking signed return and abnormal volume as the dependent variables, respectively. We present results for signed return, as it better reflects executives' incentive to leverage their credibility to elicit a favorable reaction. We follow Equation (3) as implemented in Table 6, panel B, splitting the sample on each cross-sectional variable. For signed return in panel C, we see significant results for larger firms, firms with higher current retail trading, and executives with more followers. This is consistent with higher-attention firms and executives driving the effects, as the tweets by these executives should receive

Table 7. Market Response Mechanism, Partitioned Sample Analysis

Variables	Size		Retail trading		Followers, Executive	
	≥median	<median	≥median	<median	≥90th pct	<90th pct
Panel A: Cross-sectional tests on new information and unsigned return						
<i>Unmatched financial tweets, Executive</i>	0.004 (1.41)	0.002 (1.39)	0.006** (2.14)	−0.001 (−0.66)	0.002 (1.15)	0.003 (1.54)
<i>Matched financial tweets, Executive</i>	0.005*** (5.29)	0.003* (1.77)	0.005*** (4.45)	0.003*** (2.72)	0.006*** (6.36)	0.002 (1.15)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm, executive, year, and month Fes	Yes	Yes	Yes	Yes	Yes	Yes
Difference of coefficients <i>t</i> -statistic: unmatched		0.78		2.24**		−0.50
Difference of coefficients <i>t</i> -statistic: matched		0.73		0.99		2.49**
Adjusted <i>R</i> ²	0.128	0.097	0.135	0.094	0.121	0.119
Observations	188,767	187,677	191,441	184,999	38,786	337,657
Panel B: Cross-sectional tests on new information and abnormal volume						
<i>Unmatched financial tweets, Executive</i>	0.253 (1.16)	0.052 (0.84)	0.252* (1.68)	0.003 (0.04)	0.269** (2.03)	0.055 (0.46)
<i>Matched financial tweets, Executive</i>	0.543*** (7.81)	0.129 (1.19)	0.528*** (5.16)	0.293*** (3.71)	0.573*** (8.12)	0.153 (1.58)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm, executive, year, and month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Difference of coefficients <i>t</i> -statistic: unmatched		0.89		1.41		1.20
Difference of coefficients <i>t</i> -statistic: matched		3.22***		1.81*		3.50***
Adjusted <i>R</i> ²	0.064	0.055	0.081	0.041	0.080	0.055
Observations	188,694	187,582	191,323	184,950	38,786	337,489
Panel C: Cross-sectional tests on perceived credibility and signed return						
<i>Financial tweets, Executive × Tweet similarity</i>	0.026*** (3.42)	−0.013 (−0.38)	0.023** (2.21)	0.010 (0.80)	0.022** (2.14)	−0.005 (−0.34)
All controls and main effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm, executive, year, and month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Difference of coefficients <i>t</i> -statistic		1.11		0.82		1.48
Adjusted <i>R</i> ²	0.001	0.001	0.001	−0.000	0.002	0.001
Observations	154,618	133,525	151,072	137,063	34,104	254,037
Panel D: Cross-sectional tests on perceived credibility and abnormal volume						
<i>Financial tweets, Executive × Tweet similarity</i>	1.52*** (3.13)	2.44* (1.66)	2.35*** (5.57)	1.55** (2.40)	2.15*** (3.13)	0.493 (1.12)
All controls and main effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm, executive, year, and month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Difference of coefficients <i>t</i> -statistic		−0.60		1.05		2.04**
Adjusted <i>R</i> ²	0.067	0.059	0.087	0.042	0.081	0.059
Observations	154,556	133,431	150,964	137,018	34,104	253,881

Notes. Panels A and B follow Equation (2) and are estimated based on the main regression sample, whereas panels C and D follow Equation (3) and are estimated based on a sample of all observations with at least one firm tweet in the preceding 48 hours. The table presents the results of the partitioned sample tests for executive financial tweets. In each panel, the first pair of columns presents a median split on firm size, the second pair of columns present a median split on the retail trade percentage on the trading day, and the final two columns present a split on whether the executive is in the top decile of followers for executives in our sample. We use linear regression with HDFEs. In panel A, the dependent variable is unsigned market model return on day *t*; in panels B and D, the dependent variable is abnormal volume on day *t*; and in panel C, the dependent variable is signed market model return on day *t*. The “difference of coefficients” rows document *t*-test statistics between the coefficients of each partition. All controls from Appendix B are included. All standard errors are clustered by executive and trading day. The *t* statistics are presented in parentheses. pct, percentile.

****p* < 0.01; ***p* < 0.05; **p* < 0.10.

more attention, though we caveat that differences in coefficients across partitions are not significant. In panel D, we examine abnormal volume. Here we see significant effects on both sides of the partitions for our firm-based cross-sections; however, when we examine the number of followers an executive has, we see that higher follower has a stronger effect, and the coefficient

difference is statistically significant. Taken together, these cross-sections provide modest support that attention drives the perceived credibility mechanism.

4.3. Falsification Test

It is possible that other mechanisms could explain our results. One such mechanism is repeated dissemination:

The act of repeating firms' posts leads to market reaction. If repeated dissemination is the underlying driver of our perceived credibility mechanism tests, this would be indistinguishable from the effects of perceived credibility, as the *Tweet similarity* measure would also reflect this repeated dissemination. To mitigate the concern that repeated dissemination is the mechanism behind our findings, we conduct a falsification test by constructing a measure of repeated information dissemination that is not dependent on executives' tweets. To do this, we reconstruct our *Tweet similarity* measure using firms' financial tweets as opposed to executives' financial tweets.¹⁸ In the falsification test, *Tweet similarity*^F represents the similarity between the firms' financial tweets on the trading day and the firm tweet with the most similar meaning by the same firm in the 48 hours leading up to the firm financial tweets. In this way, we capture repeated dissemination, but the repeated dissemination is by the firm itself.

We present the results for this falsification test in Table 8. We follow Equation (3) and include the same controls, fixed effects, and clustering as in Table 6, panel B. Across all five columns, we never observe a positive coefficient on the interaction term, suggesting that firm tweets are perceived differently than executive tweets. In addition, we see a negative and significant coefficient on the interaction term for unsigned return and for abnormal volume, suggesting that the market's reaction to repetition by firms may be opposite to that of executives: whereas the market reacts more and trades more around executive tweets that are

similar to prior firm tweets, the market reacts less and trades less around firm tweets that are similar to prior firm tweets. Based on this falsification test, our main finding on whether executive financial tweets move stock prices is not likely due to repeated dissemination of information alone, but rather due to the poster's identity as an executive.

5. Robustness Tests (Untabulated)

5.1. Silent Executives

As the reason executives do not tweet is unobservable, we are unable to discern why some executives in our sample remain silent on Twitter. Our main results include these executives under the assumption that they could have tweeted at any point in time. However, external factors may have prevented them from tweeting. Thus, we rerun our primary tests removing any executives who have never tweeted as of a given date. Our sample then includes only executives who have tweeted by day *t*. We also examine other cutoffs of 10 tweets and 100 tweets by day *t*. We continue to find stock market reaction around executive financial tweets across all three samples. For cutoffs of 1 and 10 tweets (100 tweets), we find statistically significant results for financial tweets for all (almost all) tests and dependent variables in Tables 3 through 5. For our mechanism tests, we see inferentially similar results for the new information mechanism using cutoffs of 1 and 10 tweets, and we see statistically equivalent or stronger results for all cutoffs for the perceived credibility mechanism. Overall, our results are robust to requiring

Table 8. Mechanism Falsification Test: Firm Dissemination

Variables	MMR _t (1)	MMR _t (2)	Abnormal volume _t (3)	Abnormal retail trading _t (4)	Retail BSI _t (5)
Financial tweets, Firm × Tweet similarity ^F	−0.004*** (−3.07)	−0.000 (−0.39)	−0.389*** (−2.59)	−0.019 (−1.07)	−0.005 (−0.47)
Financial tweets, Executive	0.004*** (4.73)	0.002* (1.76)	0.440*** (5.05)	0.038*** (2.98)	0.010* (1.77)
Financial tweets, Firm	0.004*** (3.73)	0.000 (0.33)	0.389*** (4.86)	0.010 (0.96)	0.004 (0.65)
Tweet similarity ^F	−0.000 (−0.02)	0.001 (0.86)	−0.146 (−1.18)	−0.004 (−0.24)	−0.001 (−0.14)
All controls	Yes	Yes	Yes	Yes	Yes
Firm, executive, year, and month Fes	Yes	Yes	Yes	Yes	Yes
Adjusted R ²	0.112	0.001	0.061	0.016	0.046
Observations	288,143	288,143	287,987	281,706	267,045

Notes. This table presents the results of regression Equation (3), but it uses the similarity of firms' tweets to their own prior tweets in place of the similarity between tweets by executives and tweets by their firm. The linear regressions are estimated based on a sample of all observations with at least one firm tweet in the preceding 48 hours. The dependent variables are unsigned market model return on day *t* in column (1), signed market model return on day *t* in column (2), abnormal volume following Beaver et al. (2020) in column (3), abnormal retail trading following Blankespoor et al. (2019) in column (4), and retail buy–sell imbalance following Barber et al. (2024a) in column (5). Retail trades are classified based on the Barber et al. (2024b) method. Column (5) is restricted to firm-trading days with at least 10 retail trades. All controls from Appendix B are included. All standard errors are clustered by executive and trading day. The *t* statistics are presented in parentheses.

****p* < 0.01; **p* < 0.10.

executives to have tweeted at least once, 10 times, or even 100 times.

5.2. Leave-One-Out Analysis

As the distribution of executive tweets is heavily skewed, we conduct a leave-one-out analysis, dropping each of the 262 executives with at least one tweet in the sample to examine robustness to perturbations of the sample. Replicating Table 3, we find that three dependent variables (unsigned return, abnormal volume, and retail buy–sell imbalance) are robust in all 262 samples. Signed return (abnormal retail trading) is robust in 258 (261) samples, of which three (one) of the insignificant samples involve dropping an executive in the top 10 highest tweeting individuals in our sample.

Replicating Table 6, panel A, we continue to see significant results for unsigned return and retail buy–sell imbalance across all samples. In panel B, we find significant results for abnormal volume across all samples, and we see significant results for 259 and 261 samples using unsigned and signed abnormal returns, respectively. For signed return, one insignificant sample involved dropping an executive among the top 10 highest tweeting executives in our sample. However, conducting a subsequent leave-one-out test after excluding this executive can still yield significant results, suggesting that the executive is not the sole driver of the perceived credibility mechanism. For unsigned return, two of the insignificant samples involve dropping an executive in the top 10 highest tweeting individuals in our sample.

5.3. Executives Without Matching Firm Accounts

Our main regression sample requires that both executives and their firms are on Twitter. Thus, if an executive's firm is not on Twitter at the time of an executive tweet, we do not include the observation in our sample, as there would be no control for the firm's social media activity, and the matched financial tweet and similarity measures would not be computable. In a set of robustness tests, we relax this restriction. Instead, we include executives whose firms are not on Twitter, setting all firm tweet measures to zero. We treat all such executive financial tweets as unmatched, and we set *Tweet similarity* to zero for these observations. We find that this adjustment has no effect on our main tests in Tables 3 and 6.

5.4. Robustness Tests for Mechanism Measures

Our perceived credibility mechanism results are based on using Euclidean distance (L2 norm) when computing *Tweet similarity*. We replicate our results in Tables 6 through 8 using an alternative specification based on Manhattan distance (L1 norm) for the distance measure underlying *Tweet similarity*. Using this alternative

metric, our results are inferentially identical. In addition, our similarity and matched tweet measures in our perceived credibility mechanism tests are based on a 48-hour window preceding each executive financial tweet. In a robustness check, we adjust this window from two days to one day or to seven days before each tweet by an executive. Our results are inferentially identical using a one-day or seven-day window.

6. Conclusion

This paper examines the tweeting behavior of executives of S&P 1500 firms in 2011–2018. There has been a substantial increase in the number of executives on Twitter, from 2.6% in 2011 to 12.1% in 2018. We find that most executive tweets receive no market reaction. However, financial tweets, which comprise less than 2% of all executive tweets, are associated with modest market reaction. We find an increase in unsigned and signed returns, trading volume, retail trading, and retail buy–sell imbalance associated with executives posting financial tweets. Furthermore, the increase in stock price and retail buy trades occurs when executives post nonnegative (positive and neutral) sentiment financial tweets but not when they post negative sentiment financial tweets. We also find that financial tweets posted before trading starts drive some of the effect, which limits the concern of reverse causality.

We examine the mechanism underlying the market reaction to executive financial tweets using an innovative measure based on the similarity of content between executive financial tweets and firm tweets. We find that the market reacts more around executives' financial tweets that contain content similar to that of existing tweets by their firms. This evidence supports the perceived credibility mechanism, which suggests that executive financial tweets increase the credibility of the content in tweets posted by firms by reducing investors' uncertainty. We also document that executives play a role in relaying new information on Twitter, as, in the absence of any recent tweets from their firms, executives' tweets are followed by market reaction. Collectively, our evidence suggests that both the perceived credibility mechanism and the new information mechanism play a role in facilitating market reaction to executive tweets.

Our study has several limitations. First, our inferences are based on a relatively small number of financial tweets, which account for less than 2% of all executive tweets. Moreover, not all executives in our sample use Twitter, and among those who do, only a subset tweet about financial information. As a result, our conclusions regarding financial tweets may be affected by small-sample limitations. Second, some executive tweets may be missing from our data because these tweets were deleted prior to our data collection.

Finally, our sample period spans from 2011 to 2018. Given the rapid and dynamic evolution of social media activities over time, our conclusions may need to be revisited with later years of data in future research.

This paper presents a holistic view of executive tweeting and concludes that most executives use Twitter for nonbusiness communication, but a small subset of financially relevant tweets are associated with market responses. Although it shows the extent of market reaction and the mechanism that drives market reaction to a subset of these tweets, we do not examine executives’ reasons for tweeting. As executive tweets become more popular, future research is needed to understand whether and how executives strategically use social media to move markets or influence stakeholders’ views of the firm.

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Appendix A. Top Accounts by Number of Tweets

In Tables A.1 and A.2, we present the top 10 accounts for executives (CEOs and CFOs) and firms, based on the number of tweets posted by the account during our regression sample. We also present the number of tweets posted by the account through the end of 2018. This number of tweets may underrepresent the total number of tweets in cases where the executive or firm has deleted tweets. Twitter handles are listed as of the time of collection and may have changed. After a user changes their handle, other users can reserve it. In contrast, Twitter IDs are permanent identifiers, though they can be passed to other users by handing over the account, which happened in the case of account ID 2196581568. After an account is closed, the Twitter ID will no longer point to a valid page, as in the case of account ID 3178944356; after closing, the Twitter handle gets released back to the public.

Table A.1. Top Executive Accounts on Twitter by Number of Tweets

#	Executive	Title	Company	Twitter handle	Twitter ID	# of tweets	# in sample
1	John J. Legere	CEO	T-Mobile	JohnLegere	1394399438	42,987	42,764
2	Marc R. Benioff	CEO	Salesforce.com	Benioff	22330739	21,389	21,237
3	Jack Dorsey	CEO	Twitter	jack	12	17,912	4,743
4	Jonathan Oringer	CEO	Shutterstock	jonoringer	23890475	5,261	4,607
5	Alfredo Bala	CEO	Mannatech Inc.	albala	18272589	3,940	3,903
6	Karl McDonnell	CEO	Strategic Education	Karl_McDonnell	249441251	4,870	3,501
7	J. Braxton Carter, II	CFO	T-Mobile US Inc.	braxtoncarter	2196581568	2,539	2,531
8	Patrick K. Decker	CEO	Xylem Inc.	PatrickKDecker	2697201733	2,184	2,148
9	Ron Cohen	CEO	Acorda Therapeutics Inc.	roncohenshair	2420618906	1,975	1,968
10	Eileen P. Drake	CEO	Aerojet Rocketdyne	DrakeEileen	3178944356	2,158	1,818

Table A.2. Top Firm Accounts on Twitter by Number of Tweets

#	Company	Twitter handles	Twitter IDs	# of tweets	# in sample
1	Southwest Airlines	SouthwestAir	7212562	743,331	681,713
2	McDonald’s Corp	McDonalds and McDonaldsCorp	71026122 and 111679943	721,442	662,651
3	T-Mobile US Inc.	TMobile	17338082	482,825	418,782
4	TripAdvisor Inc.	TripAdvisor	16365636	222,524	220,070
5	Nutrisystem Inc.	Nutrisystem	15038742	228,251	217,642
6	Coca Cola Co.	CocaCola and CocaColaCo	26787673 and 23482357	271,185	205,378
7	Amazon.com Inc.	amazon and amazonnews	20793816 and 818902172347678720	128,069	156,551
8	Grubhub Inc.	Grubhub	15897147	91,058	71,325
9	Altaba Inc.	Yahoo	19380829	76,083	70,582
10	Live Nation Entertainment	LiveNation	9629222	70,609	70,414

Appendix B. Variable Definitions

Variable	Definition (sources of data are listed in brackets)
Tweet count variables	
<i>Financial tweets, Executive or Financial tweets, Firm</i>	The number of financial tweets posted by the executive (or firm) during a trading day (or part thereof) as classified by the Twitter-LDA model described in Section 2.2.1 [Twitter API and Gnip]
<i>Nonfin business tweets, Executive or Nonfin business tweets, Firm</i>	The number of tweets about business-oriented topics, excluding financial topics, posted by the executive (or firm) during a trading day (or part thereof) as classified by the Twitter-LDA model described in Section 2.2.1 [Twitter API and Gnip]
<i>Other tweets, Executive or Other tweets, Firm</i>	The number of tweets posted by the executive (or firm) during a trading day (or part thereof) not included in the related <i>Financial tweets</i> and <i>Nonfin business tweets</i> measures as classified by the Twitter-LDA model described in Section 2.2.1 [Twitter API and Gnip]
<i>[Topic] tweets, Nonnegative, Executive or [Topic] tweets, Nonnegative, Firm</i>	The number of positive and neutral <i>[topic]</i> tweets posted by the executive (or firm) during a trading day (or part thereof). Positive tweets are those with a VADER score above 0.05, whereas neutral tweets have a VADER score between −0.05 and 0.05.
<i>[Topic] tweets, Negative, Executive or [Topic] tweets, Negative, Firm</i>	The number of negative <i>[topic]</i> tweets posted by the executive (or firm) during a trading day (or part thereof). Negative tweets are those with a VADER score below −0.05.
Dependent variables	
$ MMR_t $ or MMR_t	Unsigned or signed market model return on day t , calculated using a daily frequency, using a daily updated beta with respect to the S&P 500 index calculated over the prior quarter (63 trading days) [CRSP]
<i>Abnormal volume_t</i>	Abnormal volume following Beaver et al. (2020). The numerator is calculated as the volume on day t divided by the mean volume over days $[t - 130, t - 10]$ and $[t + 10, t + 130]$. The denominator is the standard deviation of volume over days $[t - 130, t - 10]$ and $[t + 10, t + 130]$. [CRSP]
<i>Abnormal retail trading_t</i>	Following Blankespoor et al. (2019), this is calculated as a ratio of the event average daily retail trade percentage to prior average daily retail trade percentage. Event retail trade percentage is calculated for the event day, whereas past retail trade percentage is calculated over the window $[t - 41, t - 11]$. Retail trade percentage is the number of retail trades, as classified following the method of Barber et al. (2024b), divided by the total number of trades on the given day. [Trade and Quote; (TAQ)]
<i>Retail BSI_t</i>	Retail buy–sell trade imbalance following Barber et al. (2024a); calculated as $2(buy_t / (buy_t + sell_t) - 0.5)$, where buy_t is the number of retail buy trades on day t , and $sell_t$ is the number of sell trades on day t [TAQ]
Mechanism variables	
<i>Unmatched financial tweets, Executive</i>	The number of executive financial tweets posted on the trading day that are not preceded by a firm tweet in the prior 48 hours [Twitter API and Gnip]
<i>Matched financial tweets, Executive</i>	The number of executive financial tweets posted on the trading day that are preceded by a firm tweet in the prior 48 hours [Twitter API and Gnip]
<i>Tweet similarity</i>	The similarity of financial tweets by an executive to the most similar tweet by the executive's firm in the 48 hours preceding the executive's financial tweet. <i>Tweet similarity</i> is calculated as $(1 - Distance/2)$ and is thus scaled to the range of $[0, 1]$, where 1 is most similar. <i>Distance</i> is measured as the minimum Euclidean distance (L2 norm) between the USE vector representing the executive's financial tweet and the USE vectors representing the tweets by the executive's firm. USE vectors are calculated as described in Online Appendix OA.4. [Twitter API and Gnip]
<i>Tweet similarity^F</i>	Calculated the same as <i>Tweets similarity</i> , except it compares financial tweets by a firm to the most similar tweet by the same firm in the 48 hours preceding the firm's financial tweet [Twitter API and Gnip]
<i>Debt</i>	Debt as a portion of assets, calculated as total liabilities (ltq) divided by total assets (atq), winsorized at 5% and 95% [Compustat]
<i>Executive age</i>	Age of the executive, in years [Execucomp]
<i>Firm event</i>	An indicator equal to one on trading days when the firm has an earnings event (earnings announcement or conference call) or an SEC filing release (form 10-K, 10-Q, or 8-K), and otherwise zero [I/B/E/S, Capital IQ, and WRDS SEC Analytics]
MMR_{t-1} or $ MMR_{t-1} $	Market model return on day $t - 1$, calculated using a daily frequency, using a daily updated beta with respect to the S&P 500 index calculated over the prior quarter (63 trading days). This is included as a signed measure when the dependent variable is MMR_t or <i>Retail BSI_t</i> , and it is included as an absolute measure otherwise. [CRSP]
<i>MTB</i>	Market to book value, calculated as market value (mkvaltq) divided by total assets (atq), winsorized at 5% and 95% [Compustat]

Appendix B. (Continued)

Variable	Definition (sources of data are listed in brackets)
ROA	Return on assets, calculated as net income (niq) divided by total assets (atq), winsorized at 5% and 95% [Compustat]
Size	Log of assets (atq), winsorized at 5% and 95% [Compustat]
Control variables (Twitter)	Note: Except for the <i>Total tweets</i> measures, these control variables are backfilled from the time of collection as historic data are unavailable from our data sources. Firm and CEO data are first available as of January 2017, and CFO data are first available as of June 2017. For accounts that joined after September 2016, all controls are backfilled based on data collected in June 2021. For days missing these measures after the first date of availability, the previous nonmissing observation is used.
$\log(\text{Followers, Executive})$ or $\log(\text{Followers, Firm})$	The log of one plus the number of Twitter accounts following the executive (CEO or CFO) or firm on Twitter [Twitter API]
$\log(\text{Following, Executive})$ or $\log(\text{Following, Firm})$	The log of one plus the number of Twitter accounts the executive (CEO or CFO) or firm follows on Twitter [Twitter API]
$\log(\text{Total tweets, Executive})$ or $\log(\text{Total tweets, Firm})$	The log of one plus the number of tweets that the executive (CEO or CFO) or firm has posted up to the given date [Twitter API]
Partitioning variables	
Retail trading	Percentage of trades by retail traders on day t . Retail trades are classified following the method of Barber et al. (2024b). [TAQ]

Endnotes

- ¹ Per Twitter’s 2021 third-quarter (Q3) letter to shareholders, the platform attracted over 211 million active users as of Q3 2021 (Twitter 2021).
- ² For instance, in our full sample 67% of executives’ tweets occur outside of trading hours, whereas only 59% of firm tweets occur outside of trading hours. We find that 46 executives only tweeted outside of trading hours, whereas no firms did so. In addition, most executive financial tweets were sent from standard Twitter clients like Twitter for iPhone or Twitter Web Client, and less than 15% were sent from enterprise or marketing Twitter clients. In contrast, over 65% of firms’ financial tweets were sent using enterprise or marketing Twitter clients.
- ³ We identify executive accounts using Twitter’s search function, Google search and LinkedIn. We verify accounts by examining user descriptions and posted tweets, cross-referencing employment against Execucomp and LinkedIn. One executive deleted their account before we could download their tweets; we drop this executive from our sample.
- ⁴ A limitation of our hand collection exercise is that it requires an executive’s account to be identifiable to a user. If an executive maintains an anonymous account by not including their name or position and company, then their account would not be captured in our exercise. However, it is unlikely that such an account would influence financial markets.
- ⁵ The total percentage of tweets flagged as by a CEO or a CFO is slightly higher than 100% because of 10 cases where an executive served both roles simultaneously. In that case, we do not double count the executive in our analyses.
- ⁶ Recent methods combine BERT modeling with unsupervised clustering to enable similar insights, such as BERTopic (Grootendorst 2022).
- ⁷ All text in square brackets has been paraphrased to remove identifying information, URLs, and nontext features. The examples of financial tweets have IDs 959404607742054400 and 593408281646870528; the examples of nonfinancial tweets have IDs 180116690552619008 and 8443063816; the examples of other tweets have IDs 2046812063 and 2324803.
- ⁸ We add the caveat that VADER is a general-purpose measure; therefore, it may not capture financial domain-specific sentiment.

- However, financial domain sentiment measures, such as in Loughran and McDonald (2011), are not intended to be used on the short-form, informal discussion on social media. Despite this, our results are unchanged using the Loughran and McDonald (2011) positive and negative word lists.
- ⁹ Examples of executive financial tweets classified by VADER include “@Allergan smashes earnings estimates, says a trial for its migraine drug succeeds [link]” (positive), “Today @NCRCorporation announced fourth quarter and full year results #Q42017 #FY2017 \$NCR: [link]” (neutral), and “NASDAQ had big technical problems on earnings calls this morn.: - (Commentary to be posted; will reschedule Q&A. [link]” (negative). Although all three messages disseminate earnings information, VADER is sensitive to their differences in tone. All text in square brackets has been paraphrased to remove identifying information, URLs, and nontext features. These tweets have IDs 960850699537010688, 961737744828567552, and 659735665865814016, respectively.
- ¹⁰ All text in square brackets has been paraphrased to remove identifying information, URLs, and nontext features. The respective IDs of the two high-similarity tweets are 643472300680052736 and 643503367021572096. The CEO’s tweet was a retweet of “Thanks [journalist’s username] for having me on @CNBC to discuss @Salesforce’s growth, the imperative for every company to undergo a digital transformation and the value @MuleSoft is delivering to our customers [CNBC link].” The firm’s closest tweet was “Thank you for the warm welcome, @ChicagosMayor! We’re proud to call Chicago home. [home emoji] [quoted tweet by the mayor].” The respective tweet IDs are 10700751255268017152 and 1069645674331889664.
- ¹¹ We measure distance using Euclidean distance (L2 norm) and implement the approximate nearest neighbor matching algorithm of Arya and Mount (1993) to efficiently compute exact matches between tweets by executives and their firms.
- ¹² In rare instances, high similarity is driven by executives’ retweets of firm tweets. However, executives rarely retweet their firms’ financial tweets, instead choosing to craft their own message. Only 4.3% of executive financial tweets are retweets.
- ¹³ We also run our return tests on intraday windows, looking at returns in the 10, 30, or 60 minutes after a financial tweet by an executive. A caveat of this design is that only tweets made during trading can be examined, because there is no intraday return defined for tweets posted outside trading hours. We do not find any statistically significant effects on these shortened windows.

¹⁴ For robustness, we also examine *Abnormal retail trading* based on retail trades as identified by the method of Boehmer et al. (2021). For such robustness tests, we limit our sample to before October 1, 2016, to avoid the measurement issues discussed in Boehmer et al. (2021).

¹⁵ This is calculated as the ratio of the effect of executive financial tweets to the effect of all financial tweets by executives and firms. The effect of executive financial tweets is calculated as the coefficient on *Financial tweets*, *Executive* multiplied by the number of executive financial tweets: $0.0043058 \times 1,139 = 4.90$. The effect of firm financial tweets is calculated as the coefficient on *Financial tweets*, *Firm* multiplied by the number of firm financial tweets: $0.001552 \times 15,121 = 23.47$. The ratio is then $4.90 / (4.90 + 23.47) = 17.27\%$.

¹⁶ We compare executive financial tweets with all tweet types by firms. This ensures that if any financial tweet by a firm is not correctly classified as financial by our Twitter-LDA approach, we still compare against that tweet.

¹⁷ Following deHaan et al. (2023), we consider interacting our independent variables and controls. As our independent variables are plausibly exogenous with our controls, we check the Pearson correlations between our independent variables and controls. All are below 0.08, except for correlations with $\log(\text{Total tweets}, \text{Executive})$. Our results are robust to including interactions between our independent variables and $\log(\text{Total tweets}, \text{Executive})$.

¹⁸ *Tweet similarity*^F is nonzero for 12,593 observations, with a mean of 0.455, which is close to that of *Tweets similarity* (0.425).

References

- Abramova I, Gipper B, Su X (2024) Shaking the faith? Global frauds and trust in capital markets. Working paper, London School of Business, London.
- Arya S, Mount DM (1993) Approximate nearest neighbor queries in fixed dimensions. *Proc. Fourth Annual ACM/SIGACT-SIAM Symp. Discrete Algorithms* (Society for Industrial and Applied Mathematics, Philadelphia), 271–280.
- Ashforth BE, Mael F (1989) Social identity theory and the organization. *Acad. Management Rev.* 14(1):20–39.
- Barber BM, Lin S, Odean T (2024a) Resolving a paradox: Retail trades positively predict returns but are not profitable. *J. Financial Quant. Anal.* 59(6):2547–2581.
- Barber BM, Huang X, Jorion P, Odean T, Schwarz C (2024b) A (sub)penny for your thoughts. *J. Finance* 79(4):2403–2427.
- Bartov E, Faurel L, Mohanram PS (2018) Can Twitter help predict firm-level earnings and stock returns? *Accounting Rev.* 93(3):25–57.
- Beaver WH, McNichols MF, Wang ZZ (2020) Increased market response to earnings announcements in the 21st century: An empirical investigation. *J. Accounting Econom.* 69(1):101244.
- Blankespoor E, deHaan E, Marinovic I (2020) Disclosure processing costs, investors' information choice, and equity market outcomes: A review. *J. Accounting Econom.* 70(2–3):101344.
- Blankespoor E, Miller GS, White HD (2014) The role of dissemination in market liquidity: Evidence from firms' use of TwitterTM. *Accounting Rev.* 89(1):79–112.
- Blankespoor E, deHaan E, Wertz J, Zhu C (2019) Why do individual investors disregard information? The role of information awareness and acquisition costs. *J. Accounting Res.* 57(1): 53–84.
- Blei DM, Ng AY, Jordan MI (2003) Latent Dirichlet allocation. *J. Machine Learn. Res.* 3(March):993–1022.
- Boehmer E, Jones CM, Zhang X, Zhang X (2021) Tracking retail investor activity. *J. Finance* 76(5):2249–2305.
- Bollen J, Mao H, Zeng X (2011) Twitter mood predicts the stock market. *J. Comput. Sci.* 2(1):1–8.
- Brandflog (2012) CEO, social media & leadership survey. Report, Brandflog, New York.
- Brown NC, Crowley RM, Elliott WB (2020) What are you saying? Using *topic* to detect financial misreporting. *J. Accounting Res.* 58(1):237–291.
- Campbell B, Drake M, Thornock H, Twedt B (2023) Earnings virality. *J. Accounting Econom.* 75(1):101517.
- Campbell J, Chen H, Dhaliwal DS, Lu H, Steele L (2014) The information content of mandatory risk factor disclosures in corporate filings. *Rev. Accounting Stud.* 19(1):396–455.
- Cer D, Yang Y, Kong SY, Hua N, Limtiaco N, John RS, Constant N, et al. (2018) Universal sentence encoder. Preprint, submitted March 29, <http://arxiv.org/abs/1803.11175>.
- Chen H, Hwang BH, Liu B, Tang Y (2025) Tweeting away firm value: How investors evaluate CEOs' use of social media. Working paper, Nanyang Technological University, Singapore.
- Crowley RM, Huang W, Lu H (2024) Discretionary dissemination on Twitter. *Contemporary Accounting Res.* 41(4):2454–2487.
- Crowley RM, Lou Y, Zhao Y (2025) Social media trending and traditional media coverage. Working paper, Singapore Management University, Singapore.
- Curtis A, Richardson VJ, Schmardebeck R (2016) Investor attention and the pricing of earnings news. Mitra G, Yu X, eds. *Handbook of Sentiment Analysis in Finance* (Optirisk Systems, London, UK), 212–232.
- deHaan E, Moon JR Jr, Shipman JE, Swanquist QT, Whited RL (2023) Control variables in interactive models. *J. Financial Reporting* 8(2):77–85.
- Dyer T, Lang M, Stice-Lawrence L (2017) The evolution of 10-K textual disclosure: Evidence from latent Dirichlet allocation. *J. Accounting Econom.* 64(2):221–245.
- Elliott WB, Grant S, Hodge F (2018) Negative news and investor trust: The role of \$Firm and #CEO Twitter use. *J. Accounting Res.* 56(5):1483–1519.
- Fritsch F, Zhang Q, Zheng X (2025) Responding to climate change crises: Firms' tradeoffs. *J. Accounting Res.* 63(5):2137–2179.
- Grootendorst M (2022) BERTopic: Neural topic modeling with a class-based TF-IDF procedure. Preprint, submitted March 11, <https://arxiv.org/abs/2203.05794>.
- Hope OK, Hu D, Lu H (2016) The benefits of specific risk-factor disclosures. *Rev. Accounting Stud.* 21(4):1005–1045.
- Huang A, Wang H, Yang Y (2023) FinBERT: A large language model for extracting information from financial text. *Contemporary Accounting Res.* 40(2):806–841.
- Huang AH, Lehavy R, Zang AY, Zheng R (2018) Analyst information discovery and interpretation roles: A topic modeling approach. *Management Sci.* 64(6):2833–2855.
- Hutto C, Gilbert E (2014) VADER: A parsimonious rule-based model for sentiment analysis of social media text. *Proc. Internat. AAAI Conf. Web Soc. Media* (Association for the Advancement of Artificial Intelligence, Washington, DC), 216–225.
- Jung MJ, Naughton JP, Tahoun A, Wang C (2018) Do firms strategically disseminate? Evidence from corporate use of social media. *Accounting Rev.* 93(4):225–252.
- Kwong L, Korn M (2012) 140 characters of risk: Some CEOs fear Twitter. *Wall Street Journal* (September 26), <https://www.wsj.com/articles/SB10000872396390444083304578018423363962886>.
- Lee LF, Hutton AP, Shu S (2015) The role of social media in the capital market: Evidence from consumer product recalls. *J. Accounting Res.* 53(2):367–404.
- Lewicki RJ, Bunker BB (1996) Developing and maintaining trust in work relationships. Kramer RM, Tyler TR, eds. *Trust in Organizations: Frontiers of Theory and Research* (Sage, Thousand Oaks, CA), 114–39.
- Long SC, Xie Y, Zhou Z, Lucey B, Urquhart A (2025) From whales to waves: Social media sentiment, volatility, and whales in cryptocurrency markets. *British Accounting Rev.*, ePub ahead of print May 16, <https://doi.org/10.1016/j.bar.2025.101682>.

- Loughran T, McDonald B (2011) When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks. *J. Finance* 66(1):35–65.
- Mkrtchyan A, Sandvik J, Zhu VZ (2024) CEO activism and firm value. *Management Sci.* 70(10):6519–6549.
- Nekrasov A, Teoh S, Wu S (2022) Visuals and attention to earnings news on Twitter. *Rev. Accounting Stud.* 27(4):1233–1275.
- Shanthikumar D, Wang QA, Wu S (2021) Does interaction on social media increase or moderate extremeness? Working paper, University of California, Irvine.
- Sprenger TO, Tumasjan A, Sandner PG, Welpe IM (2014) Tweets and trades: The information content of stock microblogs. *Eur. Financial Management* 20(5):926–957.
- Twitter (2021) Q3 2021 letter to shareholders (October 26), https://web.archive.org/web/20211026201654/https://s22.q4cdn.com/826641620/files/doc_financials/2021/q3/Final-Q3'21-Shareholder-letter.pdf.
- U.S. Securities and Exchange Commission (2008) Commission guidance on the use of company web sites. Release No. 34-58288, U.S. Securities and Exchange Commission, Washington, DC.
- U.S. Securities and Exchange Commission (2013) Report of investigation pursuant to Section 21(a) of the Securities Exchange Act of 1934: Netflix, Inc., and Reed Hastings. Release No. 69279, U.S. Securities and Exchange Commission, Washington, DC.
- Weber Shandwick (2014) The social CEO: Executives tell all. Report, Weber Shandwick, New York.
- Zhao WX, Jiang J, Weng J, He J, Lim EP, Yan H, Li X (2011) Comparing Twitter and traditional media using topic models. Clough P, Foley C, Gurrin C, Lee H, Jones G, Kraaij W, Mudoch V, eds. *Advances in Information Retrieval* (Springer, Berlin), 338–349.