ABSTRACT

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This study investigates the growing phenomenon of social bot engagement with corporate disclosures. Using hand-collected data on user interactions with corporate earnings announcement (EA) tweets, I find that bot dissemination generates positive short-term returns around EA tweets, which subsequently reverse. Additional evidence suggests that the reversal likely arises because bots amplify overreaction to firms' optimistic framing. Cross-sectional analyses show that the effect is stronger for firms with greater retail investor presence and for those with lower information transparency. Transaction-level trade evidence further indicates that retail investors are the primary drivers of the initial overreaction. A horse-race analysis against human dissemination shows that reversals occur only under bot engagement, as human interactions do not exhibit similar patterns but instead counterbalance firms' optimistic framing.

MACHINE TWEETING

by

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Abstract

This study investigates the growing phenomenon of social bot engagement with corporate disclosures. Using hand-collected data on user interactions with corporate earnings announcement (EA) tweets, I find that bot dissemination generates positive short-term returns around EA tweets, which subsequently reverse. Additional evidence suggests that the reversal likely arises because bots amplify overreaction to firms' optimistic framing. Cross-sectional analyses show that the effect is stronger for firms with greater retail investor presence and for those with lower information transparency. Transaction-level trade evidence further indicates that retail investors are the primary drivers of the initial overreaction. A horse-race analysis against human dissemination shows that reversals occur only under bot engagement, as human interactions do not exhibit similar patterns but instead counterbalance firms' optimistic framing.

Keywords: social bots, strategic disclosure, social media, earnings news, information dissemination

1. Introduction

Corporate disclosure plays a central role in capital markets by shaping how investors acquire, process, and respond to information. A substantial body of research in accounting has long examined corporate disclosure practices, including what firms disclose, how they frame information, and when and where they release it. In the era of artificial intelligence, technological advancements are reshaping disclosure landscape. Recent studies indicate that firms are adapting their disclosure strategies in response to digital innovations (e.g., Blankespoor, 2019; Cao et al., 2023; Jia et al., 2025; Donelson et al., 2025; Cheng et al., 2019). Beyond shaping disclosure content and presentation, these technologies are transforming how information is disseminated in capital markets, particularly through automated agents, or bots. Early bots functioned as subscription tools that delivered alerts to users. They later evolved to autonomously generate content, including earnings releases (Blankespoor et al., 2018), and now operate on social media platforms, where they interact with users through likes, shares, and comments. Yet despite their growing presence, relatively little is known about how social bots reshape the dissemination of corporate disclosures and influence capital market outcomes.

To understand their capital market implications, it is essential to recognize that social bots differ fundamentally from human users in both behavior and intent. Behaviorally, bots operate at scale and interact with large volumes of content at speeds and frequencies far exceeding human capacity. Their automated design enables them to disseminate information rapidly and repeatedly, often amplifying selected messages within seconds of release (Gorodnichenko et al., 2021; Boichak et al., 2018). In terms of intent, human interactions are typically driven by personal interests, informational needs, or economic incentives, whereas bots follow pre-programmed instructions to systematically promote specific types of content. These differences underscore the importance of separating bot-driven from human-driven engagement when evaluating the capital market consequences of social media disclosures.

In this study, I use hand-collected data on user interactions with firm-initiated EA tweets to investigate the presence and the impact of social bots in this recurring and economically significant disclosure setting. Specifically, I address two research questions: (1) what firm characteristics attract social bots, and (2) whether and how bot engagement with EA tweets influences capital market responses.

I focus on bot engagement with firm disclosures on Twitter (now X) for two primary reasons. First, social bots are pervasive on the platform. Twitter reported in 2014 that approximately 8.5 percent of its active monthly users were automated accounts.[1] However, subsequent research indicates this figure likely understates the actual prevalence of bots (Varol et al., 2017). A recent study in 2022 commissioned by Elon Musk during the acquisition of Twitter estimated that bot accounts represent around 11 percent of the platform's user base.[2] While the precise proportion of bots remains uncertain, there is broad agreement that bots are a persistent and significant presence on the platform.

Second, Twitter has become an important channel for corporate communication. Many firms now use the platform to release earnings announcements, provide timely operational updates, and engage directly with investors, analysts, and other market participants. Prior research shows that Twitter disclosures can reach broad audiences rapidly and complement traditional disclosure channels such as press releases and SEC filings (Blankespoor et al., 2014;

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[1] Twitter, Inc. disclosed in its 2014 second-quarter Form 10-Q filing that approximately 8.5 percent of monthly active users were likely automated accounts. The filing is available at: https://www.sec.gov/Archives/edgar/data/1418091/000156459014003474/twtr-10q_20140630.htm

[2] An external analysis commissioned by Elon Musk as part of due diligence for his 2022 acquisition of Twitter suggested that the prevalence of bots on the platform was higher than Twitter's official figures. The report is available at: https://www.cnn.com/2022/10/10/tech/elon-musk-twitter-bot-analysis-cyabra/index.html

Lee et al., 2015; Jung et al., 2018). With its extensive reach and capacity for instantaneous public sharing, Twitter is particularly susceptible to amplification by automated accounts. Such susceptibility, in turn, raises important questions about how bots may influence the visibility, dissemination, and interpretation of corporate disclosures.

Ex ante, bot engagement with firm-initiated tweets may enhance information processing by reducing investors' awareness costs and expanding the audience for these disclosures. Bots possess characteristics that allow them to influence information flow through several channels. First, bots can accelerate the dissemination of firm-initiated tweets. Because they are programmed to respond instantly to triggers such as keywords, hashtags, or specific accounts, bots can amplify content within seconds of its release (Salge et al., 2022; Glenski et al., 2018; Shao et al., 2018). Second, bots can expand the reach of EA tweets, particularly through botnets, which are coordinated networks of bots that interact with each other. In such networks, the activity of one bot can trigger engagement from others, extending the disclosure to a larger and more diverse investor audience (Boshmaf et al., 2013; Khaund et al., 2021). Third, bot engagement can increase the visibility of earnings disclosures through Twitter's recommendation algorithms, which promote tweets with higher engagement. Together, these mechanisms suggest that bot engagement can reduce information processing costs and accelerate the incorporation of earnings information into prices.

However, bot engagement may also impede information processing, particularly when disclosures are strategically framed despite being factually accurate. Prior studies suggest that managers often emphasize positive signals, downplay unfavorable aspects, or omit negative details while still providing technically accurate information (Wang et al., 2023). When bots amplify such "sugarcoated" disclosures, they may disproportionately expose investors to the firm's preferred narrative. Rapid and extensive bot promotion increases the likelihood that investors first encounter disclosures shaped by favorable framing, potentially crowding out or delaying alternative interpretations from analysts or media coverage. Moreover, bot-driven engagement can reinforce the firm's framing over time. Large volumes of superficial interactions, such as retweets and likes, repeatedly expose investors to the same narrative. This repetition may exacerbate persuasion bias—when individuals fail to discount repeated information—leading investors to perceive EA tweets as more important or credible than they actually are. Such reinforcement may hinder investors' ability to identify, evaluate, and integrate the full set of relevant information into their decisions. Thus, whether social bot engagement with firm-initiated tweets improves or impedes investors' processing of earnings information remains an empirical question.

To address this question, I analyze a sample of 8,779 firm-quarter earnings announcement tweets during the 2008–2022 period. I measure the dissemination potential of bot engagement as the total number of followers and followings of bot accounts that reply, retweet, or quote a firm's earnings announcement tweet. Bot accounts are identified using Botometer (formerly BotOrNot), which evaluates more than one thousand account-level features and assigns each account a score between 0 and 5 indicating its likelihood of automation. Consistent with prior research, I classify accounts with a score of 3.0 or higher as bots.

I begin by presenting descriptive evidence on bot and human engagement with firm-initiated earnings announcement tweets. Several observations are worth noting. First, bot engagement increases steadily during most of the sample period, indicating a growing presence of bot accounts in the dissemination of earnings information. Second, bot engagement drops sharply in 2019, which is consistent with Twitter's intensified efforts to detect and remove fake accounts and automated activity beginning that year. Third, human engagement is consistently higher than bot engagement, although the gap narrows in recent years, suggesting that automated activity has become a persistent and increasingly important component of social media interactions with corporate disclosures.

Turning to the main analysis, I examine how the market responds to bot engagement with firm-initiated earnings announcement tweets. I find that greater bot engagement is associated with stronger initial market reactions, which are subsequently followed by return reversals, consistent with the view that bot amplification distorts rather than facilitates information processing. Specifically, a one standard deviation increase in bot amplification is associated with an increase of about 26 basis points in cumulative abnormal returns during the three days surrounding the tweet date, followed by a decrease of about 10 basis points over the subsequent four trading days. Further analysis indicates that this effect occurs only among firms with negative earnings surprises, while no significant association is observed for firms with positive surprises.

Next, I examine the channel through which bot engagement with firm-initiated earnings tweets relates to market reactions. As firms often emphasize favorable aspects of performance while downplaying or omitting less favorable details, the rapid and extensive amplification of such sugarcoated disclosures by bots can mislead investors. In particular, bot-driven engagement may cause investors to view firm narratives in earnings tweets as more important or credible than they truly are. To test this channel, I examine whether the effect of bot engagement varies with the extent of sugarcoating in EA tweets. Consistent with my expectation, I find that the association between bot engagement and market reactions is stronger when firms present their earnings information in a more sugarcoated manner. Moreover, among firms with negative earnings surprises, which face stronger incentives to present disclosures in a favorable tone, the effect of bot engagement on market reactions is significant only within the high-sugarcoating subsample.

To examine how bot engagement shapes investor behavior, I focus on retail trading activity around EA tweets. Retail investors, who often face attention constraints and have limited resources to verify information, are particularly susceptible to bot-driven amplification. I argue that when bots amplify sugarcoated earnings tweets, retail investors are more likely to engage in net buying that aligns with the narrative conveyed by the firm. Consistent with this prediction, I document that greater bot-driven dissemination of EA tweets is associated with increased net buying by retail investors in the week following the tweet. Complementary intraday evidence further shows that retail trading responds to bot engagement within the first three hours after the release of an EA tweet, but the effect is not statistically significant beyond that window.

While the use of short return windows in my empirical design helps mitigate the influence of confounding events, the results may still be affected by omitted variables or self-selection. To strengthen identification, I exploit a platform-wide disruption in Twitter's bot activity policies during the first quarter of 2019 as an exogenous shock to bot dissemination. Beginning in late 2018 and intensifying in early 2019, Twitter implemented a series of enforcement measures aimed at curbing automated behavior, including the removal of large numbers of suspicious accounts and tighter restrictions on third-party API access that bots rely on to retweet, like, or reply to content. These measures resulted in a marked decline in the volume and visibility of bot-driven amplification. Using a difference-in-differences design, I document that the reduction in bot-driven amplification during 2019 Q1 is associated with a decrease in the extent of initial price overreaction and the magnitude of subsequent correction.

I conduct a series of cross-sectional analyses to investigate whether the effect of bot engagement with firm-initiated EA tweets on market reactions varies across firms, focusing on retail investor attention and information transparency. Regarding retail attention, I find that the market impact of bot engagement is more pronounced for firms that attract greater retail investor interest. This evidence is consistent with retail investors being more susceptible to the influence of bot amplification. Regarding transparency, I find that bot engagement has a stronger effect on investor response when firms exhibit lower levels of transparency. The evidence suggests that when investors have limited access to reliable information about firm fundamentals, bot-driven dissemination of favorable EA tweets is more likely to distort beliefs and influence price formation.

I perform several additional analyses to disentangle the effects of bot and human engagement. First, I include human engagement as a control and find that it is associated with stronger initial market reactions but does not contribute to subsequent return reversals. In contrast, the effect of bot engagement remains significant after controlling human interactions, suggesting that bots play a distinct role in driving the observed reversals. Further analyses show that human engagement primarily strengthens market reactions to positive earnings surprises and is concentrated in disclosures with low levels of sugarcoating. Importantly, these reactions are not followed by reversals. Overall, the evidence suggests that human engagement increases investor attention to favorable earnings news and generates stronger immediate price reactions without reversal, while bot engagement contributes to temporary price pressure that subsequently reverses.

Last, I investigate why bot and human engagement have different implications for market reactions. I first perform a univariate comparison of account characteristics and find notable structural differences between the two groups. Specifically, bot accounts tend to follow more users and attract more followers, but they are generally younger than human accounts. I then conduct a tweet–user level analysis of responses to sugarcoated EA tweets. The results show that human accounts are significantly more likely than bot accounts to provide sentiment-correcting commentary. This finding suggests that human users help counterbalance firms' selective framing, whereas bots primarily amplify the original disclosure without correction. These differences help explain why bot and human engagement have distinct implications for market reactions.

My study makes several contributions to the literature. First, it contributes to research on how technological change affects information processing by documenting the consequences of bot engagement for the dissemination of corporate disclosures. Prior studies show that innovations such as EDGAR, XBRL, and large language models influence how market participants acquire, process, and interpret information (e.g., Drake et al., 2015; Bhattacharya et al., 2018; Bertomeu et al., 2025). In contrast, this study shifts the focus from how technology improves the analysis of disclosures to how automated technology shapes their dissemination. To my knowledge, this study is the first to examine bot engagement with corporate disclosures, providing evidence that algorithmic amplification influences investor awareness and interpretation of firm communications. The findings highlight an unintended consequence of technological advances in that, while bot engagement reduces awareness costs and expands access to disclosures, it can also distort information processing by disproportionately amplifying overly favorable content.

Second, this paper extends the literature on the role of social media in markets by showing that, beyond the content of disclosure, the nature of engagement also shapes how information is disseminated and interpreted. Prior research has primarily focused on the properties of disclosures themselves, including informational content (e.g., Tang, 2018; Cao et al., 2021; Crowley et al., 2024), tone and other linguistic attributes (e.g., Bartov et al., 2018; Campbell et al., 2023; Rennekamp and Witz, 2021), and presentation features (Nekrasov et al., 2022). This study shows that bot engagement influences both the visibility and interpretation of disclosures, shaping market reactions in ways not explained by disclosure characteristics alone. This paper also connects to the emerging literature on social bots in capital markets. While prior work largely examines how bot-generated content on social media affects investor behavior (e.g., Fan et al., 2020; Hanousek et al., 2025; Campbell, 2025), this paper provides evidence that bots actively engage with firm-initiated tweets, and that such engagement influences investor perceptions.

Third, this paper contributes to the growing literature on retail investors by uncovering a mechanism through which their trading behavior is influenced. Prior research suggests that retail investors, due to limited attention, tend to rely on information that is easily accessible when making investment decisions (e.g., Barber and Odean, 2008; Hirshleifer et al., 2011; Drake et al., 2012). This study complements the literature by showing that bot engagement with firm-originated tweets increases retail attention and stimulates net buying activity. These findings demonstrate that retail investor behavior is shaped not only by the content and style of disclosures, but also by algorithmic amplification through automated engagement. The study thus provides insight into how digital technologies affect investor decision-making, particularly among retail participants who are more reliant on social media for information.

Finally, this paper provides policy implications for the regulation of technology. Regulators have expressed growing concern about the role of algorithms and automated accounts in shaping the distribution and quality of information. Recent congressional hearings on misinformation, data privacy, and the influence of social media platforms have further emphasized the urgency of these issues. This study shows that social bots can have a material impact on capital markets by amplifying overly favorable corporate disclosures, indicating that the risks posed by automated accounts extend beyond misinformation to the integrity of financial information. The results suggest the need for regulatory oversight. Specifically, requiring firms to monitor and disclose bot activity associated with their social media communications would enhance transparency and reduce investors' exposure to systematically biased information.

2. Related Literature and Hypothesis Development

2.1 Related Literature

2.1.1 Social media

Social media has become an increasingly important disclosure channel, complementing traditional avenues such as press releases and regulatory filings. Among these platforms, Twitter is widely used by firms as a tool for rapidly and directly disseminating information to a broad network of stakeholders, thus exerting a significant influence on capital markets. One stream of literature focuses on firms' use of Twitter and its implications for capital markets. For example, Blankespoor et al. (2014) show that disseminating corporate news via Twitter reduces information asymmetry and improves market liquidity. Lee et al. (2015) find that firms' activity on Twitter influences stakeholders' perceptions and mitigates the negative market reaction to product recall announcements. Cao et al. (2021) demonstrates that firms strategically highlight negative news about industry peers on Twitter to elicit favorable investor responses. Nekrasov et al. (2022) document that the use of visual elements in earnings-related tweets increases investor attention.

Another stream of research focuses not on firm-level disclosure but on the informational content embedded in Twitter activity more broadly. This literature investigates whether aggregated signals from Twitter have predictive value for financial and product market outcomes. For example, Bartov et al. (2018) find that the aggregate opinion from individual tweets can predict a firm's future earnings and announcement returns. Tang (2018) finds that customer opinions about products posted on Twitter can predict subsequent firm sales growth.

While these studies provide valuable insights into the role of Twitter, they focus primarily on the content of tweets and the associated market outcomes, with much less attention to user engagement. Yet Twitter, unlike traditional disclosure channels, is inherently interactive. Twitter users can like, comment on, or share tweets, and these engagement signals play a significant role in determining how information circulates on the platform. Specifically, engagement matters in at least two ways. First, higher engagement increases the visibility of a disclosure because Twitter’s algorithms are designed to promote tweets that generate more interaction. As a result, disclosures that attract more engagement are more likely to reach a broader audience and to circulate more rapidly. Second, engagement influences how investors perceive the underlying information. Signals such as retweets, likes, and comments serve as social cues that influence perceived credibility of a disclosure. For example, a disclosure that receives many positive interactions may appear more trustworthy or important, whereas one that attracts negative or critical comments may cause users to question the reliability or implications of the information.

In this paper, I address this gap by shifting the focus from the content of tweets to the nature and implications of user engagement with firm disclosures on Twitter. In particular, I focus on bot-driven interactions with firm-initiated EA tweets. I further investigate how such automated engagement influences market reactions and retail trading activity, thus broadening the understanding of how user engagement shapes the effectiveness of social media disclosure.

My study is related to Campbell et al. (2023), who examine the determinants and capital market effects of the viral dissemination of earnings announcement tweets. They show that certain earnings tweets, because of their tone and textual features, spread widely through organic user interactions and that such virality is associated with lower market liquidity and slower price formation. My study differs from Campbell et al. (2023) in both the type of engagement and the source of information. Specifically, I examine bot-driven engagement with firm-initiated earnings announcement tweets, such as retweets, quotes, and comments on the original disclosure. In contrast, Campbell et al. (2023) analyze user-driven amplification of earnings announcements by focusing on the volume of tweets and retweets related to a firm's earnings information, which may be generated by either human or bot accounts. Moreover, while I restrict attention to firm-initiated disclosures, Campbell et al. (2023) include all user-generated tweets containing the firm's cashtag around earnings announcements, regardless of whether the content originates from the firm itself.

2.1.2 Disclosure strategy and technological changes

Corporate disclosures have long been recognized as strategic rather than purely informative. Managers have discretion over what information to release, when to release it, and how to frame it, weighing the benefits of transparency against the potential costs of revealing information. This strategic behavior reflects a fundamental trade-off: while transparency can reduce information asymmetry and improve market efficiency, it may also expose the firm to competitive disadvantages or litigation risk (e.g., Verrecchia, 1983; Diamond and Verrecchia, 1991; Bushee and Leuz, 2005). To mitigate such risks, firms may selectively emphasize favorable elements of performance, craft narratives that guide investor interpretation (Schrand and Walther, 2000; Davis et al., 2015), or time the release of unfavorable news (deHaan et al., 2015; Michaely et al., 2016).

This view of disclosure as a strategic choice extends to the use of social media. Prior studies show that firms use Twitter not only to disseminate information but also to engage in strategic disclosure. For example, Jung et al. (2018) find that firms are less likely to disseminate quarterly earnings announcements on Twitter when the news is unfavorable and when the magnitude of the negative news is greater. In addition, Crowley et al. (2024) document that firms are more likely to tweet financially related messages around extreme negative or positive news events.

Disclosure practices, however, do not operate in a vacuum; rather, they evolve in response to technological forces. Recent research shows that firms strategically adapt their disclosures by incorporating technology-related language to shape investor perceptions and by adjusting disclosure practices to accommodate technological changes in information processing. On one hand, firms use technology-related language for strategic purposes. For instance, Cheng et al. (2019) document that firms opportunistically include blockchain-related keywords in their 8-K filings to take advantage of investors' mania about blockchain and temporarily boost stock prices. Donelson et al. (2025) show that firms with greater external financing needs tend to exaggerate their AI activities in 10-K filings, whereas some firms understate their AI investments to avoid environmental, social, and labor costs. On the other hand, firms adjust the form, frequency, and framing of disclosure as technological developments reshape how information is processed. For example, Huang et al. (2019) find that firms with poor performance are more likely to issue more XBRL extension elements to increase filing complexity. Cao et al. (2023)

find that firms tailor their language to cater to machine readers by avoiding words perceived as negative and selecting those favored by algorithms.

Although prior research has explored how technological forces affect the strategic framing of disclosures, little is known about how these forces affect *the dissemination* of strategically crafted information, particularly in the context of social media where corporate news can spread rapidly and reach broad audiences. This paper contributes to the literature by analyzing how automated engagement from bots affects the dissemination and market consequences of firm-initiated, strategically framed tweets, thus complementing nascent research on corporate communication in the digital era.

2.1.3 Social bot

A social bot is a computer algorithm that automatically generates content and engages with humans on social media, attempting to mimic and potentially influence their behavior. The intentions behind designing Twitter bots can vary widely depending on the specific goals of their creators. Prior studies show that social bots can serve both benign and malicious purposes. On the one hand, they provide beneficial services such as delivering automated news updates or assisting customers; on the other hand, they can disseminate false information, manipulate public opinion, or commit fraud (Ferrara et al. 2016; Stieglitz et al., 2017).

Computer science research demonstrates that bots can significantly amplify the visibility of information on social media platforms. Programmed to execute tasks automatically, bots can quickly spread content across vast networks, reaching a larger audience than typical human users (Salge et al., 2022, Mønsted et al. 2017). Bots achieve this amplification through actions such as liking, sharing, retweeting, and commenting, which increase both the exposure and perceived popularity of content. Since platforms like Twitter and Facebook rely on algorithms that prioritize posts with higher engagement, content that attracts more interactions, whether genuine or automated, is more likely to appear prominently in user feeds and even on trending pages. In addition to individual activity, bots frequently operate in coordinated networks, or "botnets," that simultaneously engage with the same content. This coordinated behavior manipulates platform algorithms by creating a false impression of popularity or consensus, which can trigger cascading effects as real users interact with the content, further amplifying its reach (Varol et al., 2017; Lokot et al., 2016). Besides, bots can be programmed to follow popular trends or keywords to insert the content they are promoting into relevant conversations (Ferrara, 2020). This strategy enables them to precisely target users who are already interested in specific topics, thus enhancing visibility of the content.

While a growing stream of research has examined the role of social bots in domains such as political discourse (Abokhodair et al., 2015), public health communication (Broniatowski et al., 2018), and crisis response during natural disasters (Khaund et al., 2018), their role in financial markets remains relatively underexplored. This study contributes to filling this gap by providing the first evidence that social bots actively engage with firm-originated tweets and by examining how such engagement-based amplification affects market reactions.

Emerging studies have begun to investigate the effects of bot-generated content on capital markets (Fan et al., 2020; Hanousek et al., 2025; Campbell, 2025). Specifically, Fan et al. (2020) and Campbell (2025) find that bot-generated tweets lead to stronger market responses than human-generated tweets, suggesting that bots may amplify noise trading and potentially facilitate market manipulation. Hanousek et al. (2024) use shocks to CAPTCHA implementation and solving technologies as proxies for bot activity and find that higher bot activity is associated with greater disagreement among investors.

My study differs from this work in two important respects. First, with respect to the source of content, I focus exclusively on firm-initiated disclosures. Prior studies primarily examine tweets that mention firms or tickers, many of which are generated by individual users and may contain noise or misinformation. In contrast, I focus on earnings announcement tweets posted directly from firms' official Twitter accounts, which represent formal and credible disclosures.[3] Second, with respect to bot activity, I focus on engagement-based amplification rather than content generation. Whereas existing research emphasizes the informational role of bot-created content, I study how bots engage with firm-originated disclosures through retweets, quotes, and replies, and how such engagement affects the dissemination of earnings information and subsequent market reactions. Specifically, I exploit variation in bot engagement with firms' quarterly earnings announcement tweets across firms and over time to examine the disseminating role of bots.

2.2 Hypothesis development

Firms increasingly rely on social media platforms to disclose earnings information, and prior studies show that dissemination through these channels can affect how information is incorporated into prices (Blankespoor et al., 2014; Campbell et al., 2023). Unlike traditional disclosure channels, however, social media activity is shaped not only by firms and investors but also by automated accounts. This raises the question of how engagement generated by automated accounts, or bots, influences market reactions to disclosure. Ex ante, whether bot engagement with firm-initiated EA tweets ultimately improves or impairs the information environment is unclear.

[3] While firms may frame information strategically on Twitter, they cannot misstate material facts without legal consequences given SEC oversight. As a result, earnings announcement tweets issued from official corporate accounts can be regarded as credible disclosures.

On one hand, bot engagement with firm-initiated EA tweets can facilitate information processing by reducing investors' awareness costs. Prior research shows that rapid dissemination and broader reach are often associated with lower information asymmetry and faster price discovery (Bushee et al., 2010; Drake et al., 2012).

Bots possess several characteristics that can enhance the incorporation of earnings information into prices. First, bots accelerate the spread of firm disclosures. Programmed to respond almost instantaneously to keywords or cashtags, bots can repost EA tweets within seconds, enabling the information to circulate more rapidly than if driven by human users alone (Salge et al., 2022). This immediacy increases the likelihood that investors are alerted to earnings news quickly after its release, reducing delays in initial awareness. Second, coordinated botnets expand the reach of EA tweets. While a single bot account may have limited influence, networks of bots can collectively amplify the same disclosure, ensuring that it reaches a wider and more diverse investor audience (Boshmaf et al., 2013). Third, bot engagement increases the visibility of EA tweets by interacting with platform algorithms that prioritize highly engaged content. Because Twitter promotes tweets that generate more interactions, bot-driven amplification can elevate the prominence of firm-initiated EA tweets in user feeds. This greater visibility reduces the likelihood that investors overlook the disclosure and increases the chance that it is incorporated into market prices in a timely manner. Hence, bot engagement can lower the costs of acquiring and processing information, thereby improving the speed of price discovery.

On the other hand, bot engagement with firm-initiated EA tweets may distort information processing by amplifying selective narratives. Although earnings announcements are factually accurate, they often reflect framing choices that highlight favorable elements while downplaying less favorable aspects (Schrand and Walther, 2000; Davis et al., 2015). By disproportionately amplifying such selective narratives, bots may crowd out competing interpretations and reduce the quality of price formation by promoting biased disclosure.

This distortion can arise in two ways. First, bots shape investors' initial exposure to earnings disclosure. By quickly and extensively promoting selectively framed tweets, bots can increase the likelihood that investors encounter the firm's preferred version of the earnings news before alternative interpretations become salient. Initial exposure is influential because early signals often anchor subsequent judgments (Tversky and Kahneman, 1974). When bots dominate early dissemination, they may lead investors to interpret subsequent information, such as analyst commentary or media coverage, in a biased manner. Second, bots reinforce managerial framing through repeated exposure. Large volumes of superficial engagement, such as retweets and likes, simply repeat the original disclosure without the evaluative commentary or alternative perspectives that human users often provide. This repetition increases the frequency with which investors encounter the same selectively framed message, strengthening persuasion bias by making information appear more credible or important simply because it is seen multiple times (DeMarzo et al., 2003; Mullainathan and Shleifer, 2005). As a result, investors may overestimate the informativeness of earnings announcement tweets amplified by bots, impairing their ability to integrate the full set of relevant information into prices.

Taken together, whether bot engagement in firms' EA tweets facilitates or distorts price discovery is an empirical question. I therefore state this hypothesis in the null form as follows:

H1. Bot engagement with firm-initiated earnings announcement tweets is not associated with the stock price reaction surrounding those tweets.

3. Data and Variable Measurement

3.1. Data and sample

I begin with all firms that have a year-end stock price above $5 in 2022. My sample period begins in 2008 and ends in 2022, when the platform was acquired by Elon Musk and underwent substantial changes to its policies and functionality. For each firm, I identify the corporate website and search for the official Twitter account. When a firm operates multiple Twitter accounts, I select the primary account that represents the corporation as a whole.[4] If I cannot locate a Twitter account on the corporate website, I manually search for one and, if it exists, verify its authenticity. This procedure yields an initial sample of 2,143 unique firms with verified Twitter accounts. To identify earnings announcement tweets, I begin by collecting all tweets issued by each firm during a three-day window that spans from one calendar day before through one calendar day after the EA date. This window is designed to capture firm communications that are most likely associated with the EA, including messages posted immediately prior to and following the announcement. From this set of tweets, I then apply a keyword filter, following Nekrasov et al. (2022), to isolate those that are explicitly related to the earnings announcement, which results in 31,795 tweets. Next, I use the Twitter Application Programming Interface (API) to retrieve all associated social interactions for each EA tweet, including the usernames of users who replied, retweeted, or quoted the original post.[5] This procedure produces a set of 45,028 unique users. To classify users as human or bot, I employ Botometer (formerly BotOrNot), a widely used tool in academic research for detecting automated accounts on Twitter.[6] Botometer assigns each account a score from 0 to 5 that reflects

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[4] Some firms maintain multiple official Twitter accounts for particular divisions or product lines. For example, Microsoft manages several accounts, including @Microsoft, @Microsoft Office, @Microsoft Store, and @Microsoft Azure, etc. In such cases, I retain the primary corporate account (e.g., @Microsoft), which represents the firm as a whole and is the main channel used for corporate disclosure.

[5] I initially collected the data on the users who like each tweet. However, on June 12, 2024, Twitter made likes private for all users, which resulted in incomplete data. Due to this limitation, I exclude likes from the main analysis. In untabulated robustness tests that incorporate the partial likes data, the results remain consistent.

[6] I thank Kai-Cheng Yang for kindly sharing the data used in this study.

the probability of automation, with higher scores indicating a greater likelihood that the account is a bot.[7] After merging with the Botometer scores, the final user sample contains 32,302 unique accounts. I obtain analyst forecasts and actual earnings numbers from I/B/E/S, company financial data from Compustat, and stock prices and returns from CRSP. I exclude financial firms (SIC 6000–6999) and firms headquartered outside of the U.S. as these firms operate under distinct regulatory environments. I also exclude firms with a debt ratio greater than one, firms with total book assets below $10 million, and firms that have been listed for less than one year at the time of the earnings announcement to remove extreme cases and micro-cap firms. I further drop observations with missing or incomplete financial data required to construct the variables used in the empirical analyses. All continuous variables are winsorized at 1% and 99%. After applying these filters and merging different data sets, my final sample consists of 8,779 earnings announcement tweets issued by 982 unique firms on their respective earnings announcement dates.

3.2 Measures of Bot Engagement

Following prior studies, I classify accounts with a Botometer score of 3.0 or higher as bots (Shao et al., 2017; Rizoiu et al., 2018; Pozzana and Ferrara, 2020).[8] Appendix B provides more details and examples of the bot accounts from my sample. To capture bot engagement with firm-initiated EA tweets, I construct a continuous variable, BotImpact, that measures the potential dissemination power of bot accounts. For each EA tweet, I calculate the total number of

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[7] Botometer is a state-of-the-art machine learning algorithm designed to assess whether Twitter accounts are operated by humans or bots. The algorithm analyzes more than one thousand features derived from publicly available data and account metadata, including user attributes, network connections, temporal activity patterns, content and language use, and sentiment. Based on this information, Botometer assigns each account a score indicating the likelihood of automation. Botometer has also received attention outside of academia, including its use by Elon Musk in discussions regarding the prevalence of bots on Twitter (e.g., https://www.cnn.com/2022/08/09/tech/elon-musk-twitter-botometer/index.html).

[8] The Botometer developers typically label accounts with scores above 2.5 (out of 5) as bots (e.g., Shao et al., 2018; Chang and Ferrara, 2022). However, this threshold has faced criticism, as it risks misclassifying highly active human users as bots, leading to false positives (Gallwitz and Kreil, 2022). To adopt a more conservative approach, I use a cutoff of 3.0 in my main analysis. In untabulated robustness tests, I also re-estimate the results using thresholds of 2.5 and 4.0, and the findings remain consistent.

followers and followings of all bot accounts that interacted with the tweet through replies, retweets, or quotes. This measure reflects the collective reach and amplification capacity of bot engagement, allowing for a direct evaluation of how bots may influence the dissemination and visibility of firms' EA tweets on social media.

3.3 Other variables

The primary dependent variable for my analysis is the cumulative abnormal return (CAR) over a three-day window centered on the earnings tweet date, denoted as CAR [0,2]. To examine whether bot engagement is associated with subsequent price reversals, I also calculate CAR [3,6], which measures cumulative abnormal returns from day 3 to day 6 following the earnings tweet date. I compute abnormal returns as the firm's raw return minus the average return of all firms in the same size decile and then cumulate these differences over the relevant event window.

In addition, I incorporate the following control variables in my analysis. Firm size (Logsize) is measured as the natural logarithm of total assets at the end of the fiscal quarter. Book-to-market ratio (BM) is calculated as the book value of equity divided by the market value of equity. Standardized unexpected earnings (RSUE) is defined as actual quarterly earnings per share reported by I/B/E/S minus the consensus analyst forecast, scaled by the stock price at the end of the prior fiscal quarter. RSUE is decile-ranked from 1 (lowest) to 10 (highest), capturing the magnitude of earnings surprises relative to expectations. Leverage (Lev) is measured as the ratio of total liabilities to total assets. Return on Assets (ROA) is calculated as quarterly earnings before extraordinary items divided by average total assets. Past return (MOM) is defined as the cumulative stock return from one month to one week prior to the earnings announcement date. Tangibility is defined as net property, plant, and equipment (PPE) scaled by total assets. Q4 is an indicator variable equal to one if the earnings announcement occurs in the firm's fourth fiscal quarter, and zero otherwise. Stock price volatility (Stkvol) is the standard deviation of monthly stock returns over the 12 months preceding the earnings announcement date. Analyst following (Logana) is the natural logarithm of one plus the number of analysts issuing forecasts for the firm.

4. Empirical Results

4.1 Descriptive Results

Panel A of Table 1 presents descriptive statistics for my main empirical analysis. Appendix A defines all variables. Among the 8,779 firm-quarter observations within the tweeting sample, 12.6% of the firm-initiated earnings announcement tweets receive engagement from at least one bot account through actions such as retweeting, quoting, or commenting. Conversely, engagement from human accounts is observed to be notably higher, with more than half of the EA tweets having interactions exclusively from human users. Figure 1 illustrates the time-series patterns of bot and human engagement in firm-initiated earnings announcement tweets.

In addition, I find that the influence of human accounts on EA tweet is substantially greater than that of bots. Specifically, the mean of HumanImpact is 4.011, compared to a mean of 0.953 for BotImpact. This disparity may be driven by higher engagement intensity by human users, as well as the larger follower and following networks associated with human accounts relative to bot accounts. For tweet characteristics, on average, 60.8% of EA tweets include hashtags (#), 18.5% contain user mentions (@), 27.3% reference stock tickers ($), and 88.1% include hyperlinks, and EA tweets contain an average of 11.47 words.

Panel B of Table 1 presents bot and human engagement in firm-initiated EA tweets across different industries in my sample, sorted by the proportion of bot engagement (Dum_isbot) from highest to lowest. Results show distinct patterns in bot and human engagement across different industries. Specifically, bots are more likely to target firms in industries such as Telephone and Television Transmission; Consumer Durables, and Oil, Gas, and Coal Extraction and Products. In contrast, industries such as Healthcare, Utilities, and Consumer Nondurables have lower levels of bot engagement. Human engagement, on the other hand, is highest in the industries of Consumer Nondurables, Chemicals and Allied Products, and Telephone and Television Transmission. This distribution suggests that bots and humans have different preferences when interacting with earnings announcement tweets across industries.

4.2 Univariate Analysis of Firms and Tweets with Bot Engagement

In this section, I investigate the firm characteristics associated with bot engagement in EA tweets. Specifically, I examine what firm-, tweet-, and account-specific characteristics are associated with bot engagement in EA tweet. Table 2 reports the differences between firms with and without bot engagement in their EA tweets. I use T-test to assess the mean differences between the two groups. The findings suggest that larger firms, high-growth firms, and firms with lower performance are more likely to be targeted by bots. Regarding tweet-specific characteristics, firms whose EA tweets contain more hashtags, mentions, ticker symbols, and words, but fewer hyperlinks and more positively skewed (i.e., sugarcoated) language, tend to receive greater bot engagement. Regarding account-specific characteristics, firms with longer Twitter account histories and a larger number of followers and followings are associated with higher levels of bot engagement.

4.3 Baseline Results

To examine how the market reacts to bot engagement in firm-initiated EA tweets, I estimate the following OLS regression:

$$CAR\,[m,n]_{i,t} = \alpha_0 + \beta_1 BotImpact_{i,t} + Controls_{i,t} + \varepsilon_{i,t} \quad (1)$$

Where BotImpact is measured as a continuous measure of the impact of bot engagement on EA tweet dissemination. Specifically, BotImpact is defined as the natural logarithm of one plus the total number of followers and followings of bot accounts that interact with a firm's tweet. Accounts with Botometer scores above 3.0 are classified as bot accounts. CAR [m, n] is the cumulative abnormal return (CAR) during the window [m, n] around the earnings tweet date, where daily abnormal returns are raw returns minus the average return for all firms in the same market capitalization-matched decile. I include a set of firm-level control variables to control for other factors that may affect market reactions, such as earnings surprise, firm size, book-to-market ratio, leverage, tangibility, return on assets, firm age, an indicator for the fourth fiscal quarter (Q4), analyst coverage, stock volatility, and past returns. See Appendix A for detailed definitions of all variables. To alleviate the concern that time-invariant omitted industry characteristics and time trends drive my results, I also control for industry and year fixed effects.

Table 3 reports the results of the baseline regression shown in Eq. (1). Panel A presents results for the full sample using various CAR event windows. Columns (1) to (4) report contemporaneous price responses over [0,0] and [0,2] windows around tweet date.[9] In column (1) and (3), I only include the variable of interest, BotImpact. In column (2) and (4), I further include the full set of control variables. The results show that the coefficients for BotImpact are all positive and statistically significant, suggesting that bot engagement is associated with a higher return around earnings announcement tweets. Specifically, a one-standard-deviation increase in BotImpact is associated with an increase of 26 basis points in CAR [0, 2] around the tweet date. Untabulated results indicate that the findings remain robust when using a [0,1] event window. Columns (5) and (6) report results for the period covering three to six days following

[9] Untabulated results using CAR [0,1] as the dependent variable yield consistent findings.

the tweet date. The coefficients on BotImpact are negative and statistically significant, indicating a return reversal during this post-event window. Specifically, the coefficient on BotImpact in the CAR [3,6] regression is –0.0004, suggesting that the initial positive abnormal returns associated with bot engagement partially reverse in the days following the earnings announcement tweet.

Collectively, the evidence in Panel A of Table 3 suggests that bot dissemination is associated with an increase in initial market reactions, followed by a return reversal. To examine whether the effect of bot engagement in EA tweets on market reactions varies with the nature of earnings news, I partition the sample based on the sign of the earnings surprise. I then estimate the baseline regression model separately for each subsample. Panel B of Table 3 reports the regression results for firms with positive and negative earnings surprises, respectively. The results show that the effect of bot engagement in EA tweets on market reactions is observed only among firms with negative earnings surprises, indicating that bot engagement has a stronger influence on investor response when the earnings news is unfavorable. Specifically, for firms with negative earnings surprises, higher bot engagement is associated with an initial increase in returns around the earnings announcement tweet, followed by a partial reversal in the subsequent days. In contrast, for firms with positive earnings surprises, the relationship between bot engagement and market reaction is not statistically significant.

4.4 Sugarcoating and the Impact of Bot Engagement

To explore the conditions under which bot dissemination has a stronger impact on market reactions, I examine the role of sugarcoated tone in firms' earnings disclosures. I split the sample based on the extent to which firms sugarcoat earnings information. To capture sugarcoating behavior, I construct a measure based on the divergence between the tone of a firm's earnings announcement tweet and its underlying earnings performance. Specifically, I compute the difference between the decile rank of tweet sentiment and the decile rank of standardized unexpected earnings (SUE). The sentiment rank reflects the relative optimism in the language used in firms' earnings announcement tweets, while the SUE rank proxies for the firm's actual earnings performance relative to expectations. A positive value of the sugarcoat measure indicates that the tone of the disclosure is more optimistic than the earnings outcome would suggest. Finally, within each fiscal-quarter, firms above the sample median of this divergence measure are classified as high sugarcoating firms, while those below the median are classified as low sugarcoating firms. Appendix C presents illustrative examples of firm-initiated sugarcoated earnings announcement tweets from my sample.

Panel A of Table 4 compares the effect of bot engagement in EA tweets on market reactions between high and low sugarcoating firms. Column (1) shows that among high sugarcoating firms, BotImpact is positively and statistically significantly associated with CAR [0,2], indicating that bot engagement increases short-term stock returns when firms use overly optimistic language in their EA tweets. Column (2) shows that the coefficient on BotImpact for CAR [3,6] is significantly negative, suggesting a return correction as the market revises its initial reaction. In contrast, Columns (3) and (4) show that, among low sugarcoating firms, the coefficients on BotImpact are statistically insignificant in both windows, which suggests that bot engagement does not materially affect market reactions when the tone of EA tweets more closely reflects the firm's underlying earnings performance. Overall, these findings suggest that the effect of bot activity in firm-initiated EA tweets on investor responses is conditional on the degree of tone-earnings misalignment.

To further investigate whether the influence of bot engagement is more pronounced when firms have stronger incentives to distort the tone of their EA tweets, I restrict the sample to firms with negative SUE and re-estimate the moderating effect of tone sugarcoating. Panel B of Table 4 presents the results. Among firms with negative earnings surprises, the effect of bot engagement on market reactions, including both the initial price increase and the subsequent reversal, is significant only within the high sugarcoating subsample. This suggests that investors are more likely to be misled and misprice the firm's value when bots amplify a distorted message arising from an overly optimistic tone used to report poor performance. In contrast, as shown in Panel C of Table 4, I find no statistically significant coefficient of BotImpact among firms with positive earnings surprises, regardless of the level of sugarcoating tone. Taken together, the results in Table 4 indicate that the market impact of bot engagement depends on both the tone-earnings misalignment and the presence of bad news, where such misalignment is more likely to mislead investors.

4.5 Investor Trading Responses to Bot Engagement

4.5.1 Daily Trading Responses

Thus far, I have demonstrated that bot engagement in firm-initiated EA tweets is associated with stronger initial market reactions, followed by subsequent reversals. To better understand the mechanism underlying these price dynamics, this section examines the trading behavior of retail investors surrounding EA tweets.

Building on prior literature showing that retail investors face attention constraints, possess limited resources to verify information, and are more susceptible to social influence (e.g., Barber and Odean, 2008; Hirshleifer et al., 2011; Blankespoor et al., 2014), I argue that retail investors are particularly vulnerable to overly optimistic, or "sugarcoated," EA messages. When such content is amplified by bots, its visibility and apparent popularity are artificially enhanced. This amplification increases the perceived credibility of the message and raises the likelihood that retail investors interpret the announcement more favorably than warranted by fundamentals. Accordingly, I hypothesize that bot engagement with EA tweets leads to net buying pressure from retail investors following the tweet.

I follow Boehmer et al. (2021) to identify retail trades using Trade and Quote (TAQ) data and classify trade direction (buy or sell) based on the quote midpoint algorithm proposed by Barber et al. (2024). To calculate the daily retail buy–sell imbalance, I aggregate trades at the stock-day level and define the marketable retail trading measure as the difference between the number of retail buy and sell trades, scaled by the total number of retail trades.

Table 5 reports regression results examining the relation between bot engagement and retail trading activity. The coefficient on BotImpact is consistently positive and statistically significant over the seven days following the EA tweet, with the strongest effect observed on Day 1. These results suggest that greater bot-driven dissemination of EA tweets is associated with sustained net buying by retail investors, consistent with the notion that they are influenced by sugarcoated earnings information amplified by bots.

4.5.2 Intraday Retail Trading Responses

To provide further evidence that investors are influenced by bot-driven dissemination of biased tweet content, I examine the intraday dynamics of retail trading activity following firm-initiated EA tweets.

Social bots are computer algorithms programmed to autonomously generate content and interact with users in real time. As such, they can engage with and disseminate firm-initiated tweets immediately upon release. This immediacy suggests that any influence bots exert on investor behavior is likely to emerge shortly after the EA tweet is posted. While the initial amplification occurs almost instantaneously, its effects may persist a short period, as bots continue to replicate and broadcast the content and retail investors require time to observe and react. Therefore, I expect retail trading activity to increase shortly after the EA tweet in response to bot engagement. However, as market participants begin to process earnings information, the influence of bot-driven amplification is expected to fade.

Table 6 presents regression results where the dependent variable is the retail buy–sell imbalance, measured over consecutive 45-minute intervals after the tweet. Columns (1) through (4) of Table 6 show that the coefficient on BotImpact is positive and statistically significant during the first four intervals (i.e., 0 to 180 minutes post-tweet), indicating that bots influence retail trading behavior almost immediately, with the effect persisting for up to three hours. In contrast, Column (5) shows that the coefficient is no longer statistically significant beyond the three-hour window, suggesting that the retail response to bot-amplified content attenuates over time.

4.6 Robustness check

While the use of short return windows in my empirical design helps mitigate the influence of confounding events, concerns remain regarding potential endogeneity. Specifically, unobservable firm characteristics or self-selection may jointly influence both bot activity and investor responses. For example, firms with higher investor visibility or broader media coverage may attract more bot engagement and stronger market reactions. To strengthen identification, I implement a difference-in-differences design that exploits a platform-wide disruption in Twitter's bot activity policies during the first quarter of 2019. Beginning in late 2018 and accelerating in early 2019, Twitter enacted a series of enforcement measures aimed at curbing automated behavior, such as removing large numbers of suspicious and bot accounts and tightening restrictions on third-party API access that bots use to retweet, like, or reply to content. These measures led to a substantial decline in volume and visibility of bot-driven amplification. Consistent with this disruption, Figure1 shows a marked decrease in bot engagement with firm-initiated EA tweets in 2019, which validates the use of 2019Q1 as an exogenous shock to bot dissemination activity. I estimate the following model:

$$CAR[0,2]_{i,t} - CAR[0,6]_{i,t} = \alpha + \beta_1 Treat_i + \beta_2 Post_t + \beta_3 Treat_i \times Post_t + Controls + \varepsilon_{i,t} \quad (2)$$

where Post equals one if the EA tweet occurs after the first quarter of 2019, and 0 otherwise. Treat is an indicator equal to one for firms with above-median bot exposure prior to the 2019Q1 shock, and zero otherwise. Bot exposure is measured as the firm's average number of interactions, including quotes, retweets, and replies, per earnings-related tweet before 2018. Each tweet's engagement is weighted by the firm's frequency of EA tweets during the pre-period to reflect persistent dissemination activity. The dependent variable, CAR [0,2] −CAR [0,6], captures the degree of short-term return reversal following the EA tweet. A larger value indicates that the initial price reaction (days 0 to 2) is followed by a greater reversal in the subsequent period (days 3 to 6). The key variable of interest is the interaction term, Treat × Post, which captures the differential change in return reversal for high bot-exposed firms relative to low bot-exposed firms after the 2019Q1 policy shift. I expect a significantly negative coefficient on the interaction term, since a decline in bot-driven amplification would reduce the extent of initial overreaction and subsequent price correction. Other control variables are the same as in the main regression.

I estimate the model using three progressively broader sample windows to ensure robustness. The results are reported in Table 7. In Columns (1) – (2), I restrict the post-treatment period to 2018Q2–2020Q1. Columns (3) – (4) extend the window to 2018Q1–2020Q2, and Columns (5) – (6) further expand it to 2017Q4–2020Q3. Consistent with my expectation, the coefficient on the interaction term Treat × Post is negative and statistically significant across all specifications. These findings provide causal evidence that bot-driven amplification of firm-initiated EA tweets contributes to short-term price overreactions followed by subsequent reversals.

5. Additional tests

5.1 Cross-Sectional Analyses

As I noted earlier, bot-driven amplification of sugarcoated earnings information shapes retail investor trading behavior. In this section, I examine whether the effect of bot engagement with firm-initiated EA tweets on market reactions varies across firms. Specifically, I explore how retail investor attention and information transparency moderate the relation between bot engagement and investor response.

With respect to retail investor attention, I posit that the market impact of bot engagement is more pronounced for firms that attract greater retail investor attention. When retail investors are more likely to be exposed to and engage with a firm's tweets, the influence of bot-driven amplification of sugarcoated EA tweets tends to be stronger. To proxy for retail attention, I employ two measures. First, I use the visibility of a firm's official Twitter account, measured by the number of followers and followings. Greater visibility increases the likelihood that a firm's tweets are disseminated broadly and noticed by retail investors, thereby serving as a proxy for retail investor attention. Second, I use stock return volatility, since firms with more volatile prices are more likely to draw the interest of retail traders seeking trading opportunities.

In terms of information transparency, I argue that the bot-driven amplification has a stronger effect on investor response when firms exhibit lower transparency. In such settings, investors have limited access to reliable information about firm fundamentals and may rely more on easily accessible disclosures, such as EA tweets. As a result, the dissemination of sugarcoated information by bots is more likely to distort investor beliefs and influence price formation. Consistent with prior literature, I use two proxies for transparency. The first is the extent of earnings management, calculated as the sum of a firm's decile ranks in real earnings management and discretionary accruals, where higher values indicate greater manipulation and lower transparency.[10] The second is firm size, with smaller firms generally associated with weaker information environments and lower investor visibility.

For each moderating variable, I partition the sample into high and low groups based on the within-quarter median value and estimate the baseline regression model on each subsample. Results are reported in Table 8. Panel A reports subsample regression results based on proxies for retail attention, measured by Twitter visibility and stock price volatility. High- (low-) Twitter visibility firms are defined as those with the number of followers and followings on the firm's official Twitter account above (below) the sample median within the same fiscal-year quarter. High- (low-) stock price volatility firms are defined as those with a standard deviation of monthly stock prices in the past year above (below) the sample median within the same fiscal-year quarter. Panel B reports subsample regression results based on proxies for information transparency, measured by earnings quality and firm size. High- (low-) EM firms are defined as those with earnings management above (below) the sample median within the same fiscal-year quarter. Small (large) firms are defined as those with the natural logarithm of total assets below (above) the sample median within the same fiscal-year quarter. I find that the coefficient on BotImpact is statistically significant only for firms with greater retail investor attention and lower information transparency. Taken together, these findings suggest that bot amplification has

[10] Discretionary accruals are estimated following Dechow et al. (1995), and real earnings management is measured following Roychowdhury (2006).

a greater impact on market outcomes when investors are more likely to incorporate firm-initiated EA tweets into their decision-making process.

5.2 Horserace Between Bot and Human Engagement

In prior sections, I demonstrate that bot engagement with firm-initiated EA tweets significantly influences market reactions by amplifying sugarcoated information. A natural follow-up question is whether human engagement has a similar effect on investor response, and whether the observed effects of bot activity remain after controlling for human-driven interactions. To address these questions, I conduct a set of horse race analyses that compare the relative effects of bot and human engagement on market reactions to EA tweets.

First, I include human engagement as an additional explanatory variable in the baseline regression model. Panel A of Table 9 presents the regression results. As shown, the coefficient on HumanImpact is positive and statistically significant over the first two days after the EA tweet, indicating that greater human engagement with firm-initiated EA tweets is associated with stronger initial market reactions. However, the coefficient is not significant in the subsequent window, i.e., CAR [3,6], suggesting that human engagement does not drive subsequent return reversals. This pattern suggests that while human engagement can boost initial investor attention and market response, it is less likely to spread overly optimistic content that leads to subsequent price reversals. Importantly, results show that the coefficient on BotImpact remains statistically significant and directionally consistent with prior findings after controlling for human engagement, which suggests that the effect of bot engagement on market reactions is not explained by concurrent human interactions. Rather, bots appear to play a distinct role in subsequent return reversals.

Second, I investigate whether the effect of human engagement varies with the sign of earnings surprises. Panel B of Table 9 reports the results. I find that the coefficient of HumanImpact is positive and statistically significant only for firms with positive SUEs in the two-day window following the EA tweet and remains insignificant for negative SUE firms and the subsequent return window. These findings suggest that human users interact with firm-initiated EA tweets differently from bots. Unlike bots, which mechanically disseminate content, human users are more likely to add subjective interpretation when engaging with information. For firms with positive SUEs, such interpretive engagement increases investor attention to earnings news, resulting in stronger immediate market reactions without subsequent reversals.

Third, to further explore the nature of human engagement, I examine whether its market impact varies with the degree of sugarcoating in firm-initiated EA tweets. As discussed earlier, human users are more likely to incorporate subjective judgment when engaging with EA tweets. Therefore, I predict that for firms with low levels of sugarcoating, human engagement is positively associated with initial market returns and does not lead to subsequent reversals. In such cases, human interactions are likely to help reinforce information that aligns with underlying fundamentals. In contrast, for firms with highly sugarcoated tweets, I expect an insignificant coefficient on HumanImpact, since the corrective nature of human commentary may mitigate the influence of the firm's overly optimistic tone, thus reducing its impact on short-term market responses.

Table 9 Panel C reports the results. Consistent with my expectations, the coefficient on HumanImpact is positive and statistically significant in the CAR [0,2] window and insignificant in the CAR [3,6] window for firms with low levels of sugarcoating. In contrast, for firms with high sugarcoating, the coefficient on HumanImpact is insignificant in both event windows.

5.3 Correction in Bot and Human Engagement

Collectively, my findings indicate that bot and human interactions with firm-initiated tweets influence price dynamics in distinct ways. Bot accounts tend to disseminate firm disclosures in a mechanical and uncritical manner, which amplifies the effects of sugarcoated content. As a result, bot engagement is associated with a short-term increase in stock prices, followed by a reversal as the market corrects the initial overreaction. In contrast, human users are more likely to engage critically with firm communications by offering subjective assessments or expressing skepticism, particularly when the tone of the disclosure is overly optimistic. Such engagement increases investor attention and generates stronger immediate market reactions, and is associated with a more persistent response without subsequent reversals.

To examine why bot and human engagement have different implications for market reactions, I conduct two additional analyses. First, I perform a univariate comparison of account characteristics. Panel A of Table 10 reports descriptive statistics for human and bot accounts. Bot accounts tend to have more followers and follow more users, but are, on average, younger than human accounts. These differences highlight structural variation across account types that may influence how information is distributed and interpreted on social media.

Second, I conduct a tweet–user level analysis to test whether human accounts are more likely than bot accounts to issue sentiment-correcting commentary in response to sugarcoated firm tweets. I estimate the following pooled OLS regression model:

$$Correction_{i,j} = \alpha_0 + \beta_1 isBot_i + Controls_j + \varepsilon_{i,j} \qquad (3)$$

where Correction is defined at the user–tweet level and equals one if user i's quote or comment on firm tweet j expresses more negative sentiment than the original tweet, conditional on the tweet being sugarcoated. It equals zero for direct retweets without additional text or when the user's sentiment is not more negative than the firm's original message. The key independent variable, isBot, is an indicator equal to one if user i is classified as a bot, and zero otherwise.

Panel B of Table 10 reports the results. The coefficient on IsBot is negative and statistically significant, indicating that bots are significantly less likely than humans to issue sentiment-correcting interactions. These findings are consistent with the notion that bots tend to disseminate firm disclosures without independent judgment, while human users are more likely to evaluate and potentially counter overly optimistic messaging. Taken together, the differences between bot and human accounts help explain why bot and human engagement have distinct implications for market reactions.

6. Conclusion

The growing presence of bots on social media platforms has attracted considerable attention in recent years. Since bots can rapidly disseminate information to a broad set of investors, it is crucial to examine whether and how they shape the interpretation of firm disclosures. Despite this potential influence, we know little about the role of social bots in the dissemination of corporate disclosures and their consequences for capital market outcomes.

In this study, I use hand-collected data on user interactions with firm-initiated EA tweets to investigate the presence of social bots and their impact on earnings disclosure outcomes. I find that greater bot engagement is associated with stronger initial market reactions and subsequent reversals, which suggests that bot amplification distorts rather than facilitates information processing. This effect is stronger when firms present their earnings information in a more sugarcoated manner. To strengthen identification, I exploit a platform-wide disruption in Twitter's bot activity policies during the first quarter of 2019 as an exogenous shock to bot dissemination, and the results corroborate the documented findings. Using transaction level data, I further show that greater bot-driven dissemination of EA tweets is associated with increased net buying by retail investors during the week of the tweet and within the first three hours after its release. Cross-sectional analyses indicate that the effect of bot engagement on market reactions is stronger for firms with greater retail investor attention and lower information transparency. In addition, I document that the observed effects of bot engagement cannot be attributed to concurrent human interactions, which appear to play a distinct role. In particular, human accounts are more likely to provide sentiment-correcting commentary, thus counterbalancing firms' selective framing and facilitating information processing.

This study is the first to examine bot engagement with firm-initiated tweets, providing direct evidence that algorithmic amplification influences investor awareness and the interpretation of disclosures. By documenting the consequences of bot engagement for the dissemination of corporate information, the study contributes to research on how technological change affects information processing. It also extends the literature on the role of social media in capital markets by showing that, beyond the content of disclosure, the nature of engagement plays a critical role in shaping how information is disseminated and interpreted. Finally, the findings carry timely policy implications. The evidence shows that social bots can materially affect capital markets by amplifying overly favorable corporate disclosures, suggesting that the risks posed by automated accounts extend beyond misinformation to the integrity of financial information. These results highlight the importance of regulatory oversight in the digital information environment.

Appendix A. Variable Definitions

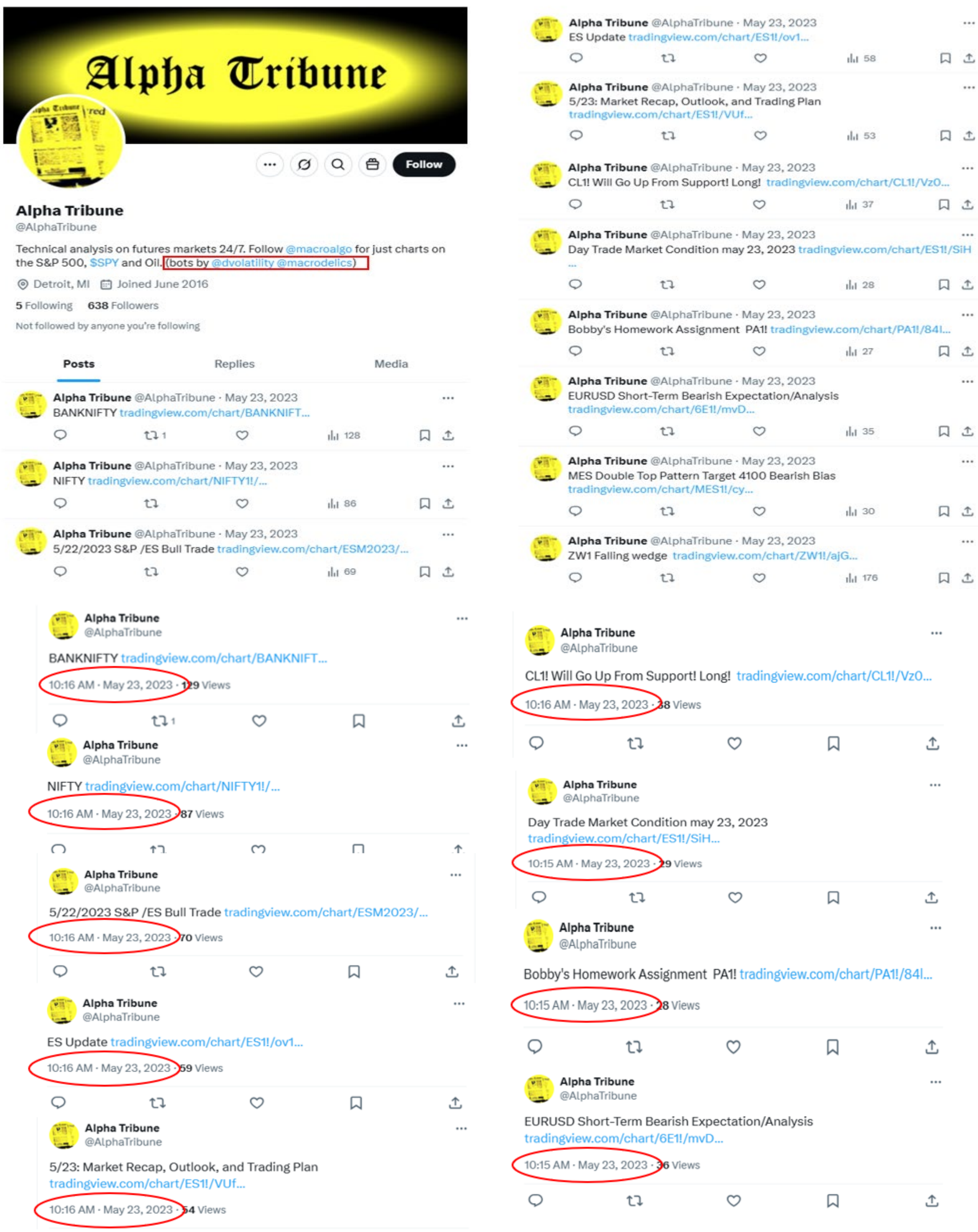
Variable Name	Definition
BotImpact	Natural logarithm of one plus the total number of followers and followings of bot accounts that engage with a firm's tweet through a retweet, quote, or comment. Accounts with Botometer scores above 3.0 are classified as bot accounts.
HumanImpact	Natural logarithm of one plus the total number of followers and followings of human accounts that engage with a firm's tweet through a retweet, quote, or comment. Accounts with Botometer scores lower than 3.0 are classified as human accounts.
CAR [m, n]	Cumulative abnormal return relative to day *t* over the window from day *m* to day *n*, where day *t* is the date of the firm-initiated earnings announcement tweet. Abnormal returns are computed as the raw return minus the average return of all firms in the same size decile.
Dum_isbot	An indicator variable is set to one if at least one bot account engages with a firm-initiated earnings announcement tweet through a retweet, quote, or comment, and zero otherwise. Accounts with Botometer scores greater than 3.0 are classified as bot accounts.
Dum_onlyhuman	An indicator variable set to one if all accounts that engage with a firm-initiated earnings announcement tweet through a retweet, quote, or comment are classified as human, and zero otherwise. Accounts with Botometer scores below 3.0 are identified as human accounts.
Num of hashtags (#)	Total number of hashtags present in the Earnings Announcement tweet.
Num of mentions (@)	Total number of user mentions present in the earnings announcement tweet.
Num of links	Total number of URLs present in the earnings announcement tweet.
Num of tickers ($)	Total number of ticker symbols mentioned as hashtags in the earnings announcement tweet.
Num of words	Natural logarithm of the total number of words in the earnings announcement tweet, excluding stop words.
Logsize	Natural logarithm of total assets.
BTM	Ratio of the book value of equity to the market value of equity.
Lev	Total liabilities divided by total assets.
Tangibility	Property, plant, and equipment scaled by total assets.
RSUE	Decile-ranked standardized unexpected earnings. Standardized unexpected earnings is calculated as actual quarterly earnings reported by I/B/E/S minus the consensus analyst forecast, scaled by the stock price at the end of the prior fiscal quarter.
ROA	Earnings before extraordinary items scaled by average total assets.

MOM	Cumulative stock return from one month to one week prior to the earnings announcement date.
Q4	An indicator variable is set to one if the earnings announcement occurs in the firm's fourth fiscal quarter, and zero otherwise.
Stkvol	Standard deviation of monthly stock returns over the 12 months preceding the earnings announcement date
Logage	Natural logarithm of the number of years since the firm's record first appears in Compustat.
Logana	Natural logarithm of one plus the number of analysts issuing forecasts for the firm
Sugarcoat_sentiment_rank	Difference between the decile rank of tweet sentiment and the decile rank of standardized unexpected earnings.
Retail_BuySell_Imbalance _Day t	Difference between the number of retail buy and sell trades on day *t* relative to the release of an earnings announcement tweet, scaled by their sum. Retail trades are identified using the methodology developed by Boehmer et al. (2021), and trade direction (buy or sell) is classified following the quote midpoint-based algorithm proposed by Barber et al. (2024).
Retail_BuySell_Imbalance _[m,n]	Difference between the number of retail buy and sell trades over the intraday window from *m* to *n* minutes relative to the release of an earnings announcement tweet, scaled by their sum. Retail trades are identified using the methodology of Boehmer et al. (2021), and trade direction (buy versus sell) is classified following the quote midpoint–based algorithm of Barber et al. (2024).
Treat	An indicator variable is set to one for firms with above-median bot exposure prior to the 2019Q1 shock, and zero otherwise. Bot exposure is measured as the firm's average number of interactions, including quotes, retweets, and replies, per earnings-related tweet before 2018.
Post	An indicator variable is set to one if the EA tweet occurs after the first quarter of 2019, and 0 otherwise.
IsBot	An indicator variable is set to one if the user is classified as a bot account and zero otherwise.
Correction	An indicator variable is set to one if user's quote or comment on firm tweet expresses more negative sentiment than the original tweet, conditional on the tweet being favorably framed. The variable equals zero for direct retweets without additional text or when the user's sentiment is not more negative than the firm's original message.

Appendix B. Examples of Bot Accounts

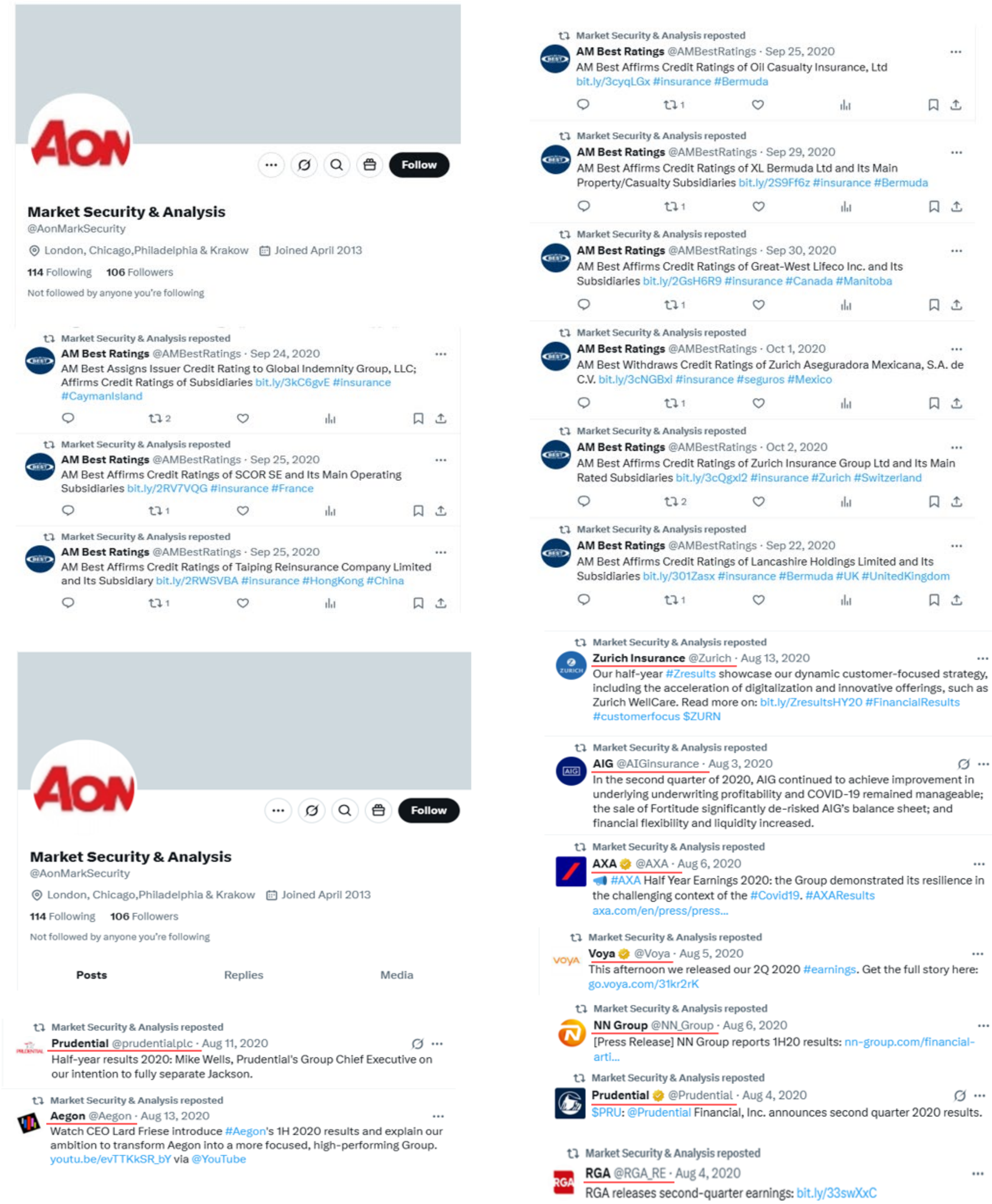
(1) Example 1

The account’s profile explicitly discloses that it uses bots. Besides, the account posts large volumes of trading-related messages within seconds of each other (e.g., multiple tweets timestamped 10:15–10:16 AM on May 23, 2023). The account has a Botometer score of 4.7/5.0.



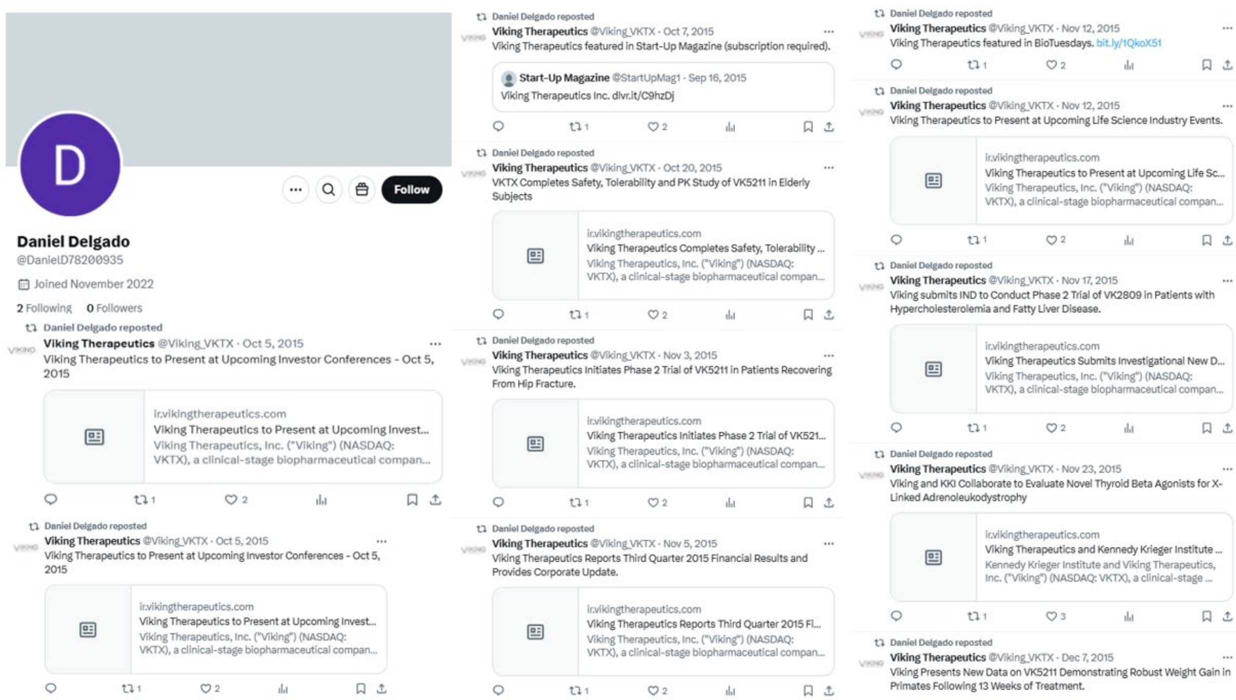
(2) Example 2

The account primarily reposts content from corporate and financial news sources without adding any original commentary. Much of its activity consists of systematically retweeting credit ratings and financial announcements from a small set of accounts (e.g., AM Best Ratings, Prudential, AIG, AXA). The account has a Botometer score of 4.2/5.0.



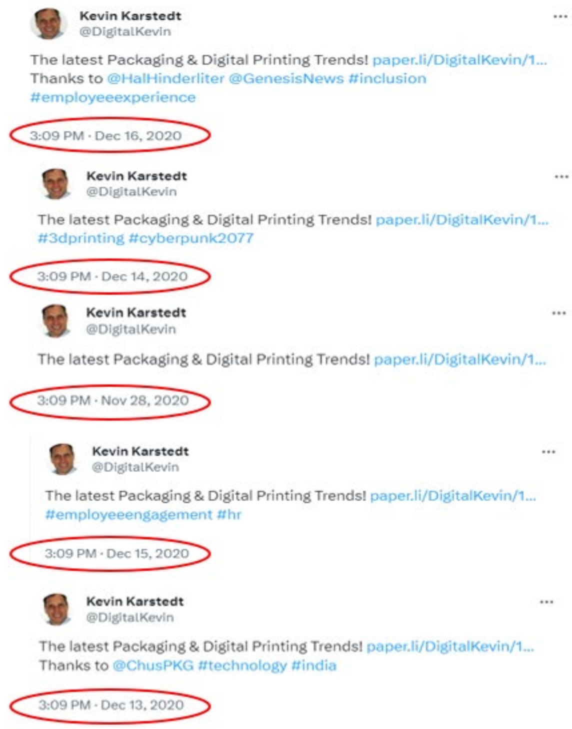
(3) Example 3

The account repeatedly reposts content from a single firm (Viking Therapeutics) within very short intervals and across multiple dates, with little to no original activity. Such repetitive, one-sided posting behavior is consistent with automated amplification. The account has a Botometer score of 4.1/5.0.



(4) Example 4

The account posts highly repetitive messages (‘The latest Packaging & Digital Printing Trends!’) on different days but always at the exact same time (3:09 PM). This systematic, clock-like posting pattern is indicative of automated scheduling rather than organic user activity. The account has a Botometer score of 4.8/5.0.



Appendix C. Example of Sugarcoated Earnings Announcement Tweets

Tweet ID	Text	SUE	Date
1255466199028293634	General Dynamics today reported quarterly net earnings of $706 million on **$8.75 billion in revenue**. Backlog of $85.7 billion, up 24% from the year-ago quarter. Read more: https://gd.com/Articles/2020/04/29/general-dynamics-reports-first-quarter-2020-results	-0.001	29-Apr-20
1057633507017551873	McDonald's has been implementing self-order kiosks in restaurants around the globe, and it's paying off. See how this tech contributed to their Q3 earnings: https://dbdnx.co/2OX7Ug4	-0.099	31-Oct-18
989143459247386625	...This is an exciting time for USG because now, as a pure manufacturer, we have the opportunity and available capital to focus on **growth** and **shareholder value creation** with a balance sheet that supports our plan. Read our Q1 2018 earnings results: https://bit.ly/2vJuAam	-0.002	25-Apr-18
1261355721305841665	VF reports Q4 earnings with a **2% increase in revenue** for the full fiscal year 2020 up to $10.5 billion.	-0.001	15-May-20
827535599812751360	Today $WY reported Q4 net earnings to common shareholders of $551 million, or $0.73 cents per diluted share. http://investor.weyerhaeuser.com/2017-02-03-Weyerhaeuser-reports-fourth-quarter-full-year-results	-0.001	3-Feb-17
1528750913426722816	We are focused on **improving our structural gross margin** and will capitalize on the opportunities to **cement our leadership position with a growing market share**. $XPEV #Earnings #XPENGByNumbers	-0.007	23-May-22
1526551480647680000	We kicked off 2022 with very strong growth momentum, closing Q1 2022 with the **highest GMV & Order growth rates** of the past 9 quarters, up 27% and 40% YoY respectively."1/4 $JMIA #JMIA #Earnings	-0.009	17-May-22
1590686855242170372	This morning, we announced our 3rd quarter earnings and provided a business update, including our upcoming WVE-N531 data in #Duchenne, our progress advancing WVE-006 for #alpha1 to the clinic and continued expansion of our platform capabilities. Click below to read more. $WVE	-0.024	10-Nov-22
994641487165083649	A great read prior to $ZIOP and $XON Q1 Earnings Calls this afternoon: Controlling CAR-T: **How scientists plan to make the engineered T cell**	-0.006	10-May-18

	therapy safer, and work for more cancers - https://bit.ly/2InPlgK #WorldWithoutCancer		
1357105810287960066	This morning, we reported our fourth quarter and full year 2020 financial results, which showed **total revenues** of $13.4 billion in 2020. A replay of our webcast is now available: #Earnings $BIIB	-0.001	3-Feb-21
1027674101115047936	Q2 Earnings: "Sunrun makes going #solar simple and we are **committed to creating an exceptional customer experience** because our customers have chosen to be with us for decades." Sunrun CEO @LynnJurich	-0.021	9-Aug-18
1589768349135044608	$TWOU - Q3 **strong performance** is a result of a **great team executing on a winning platform strategy** with @edXonline at the center. #NoBackRow	-0.016	7-Nov-22
537251447037886464	We had a **successful quarter** in **winning business and serving our customers**: Daktronics Announces Q2 FY15 Results http://investor.daktronics.com/releasedetail.cfm?ReleaseID=884777	-0.004	25-Nov-14
793549546521583616	We have reported our **best quarterly results since 2014**. Full release: http://prnewswire.com/news-releases/united-states-steel-corporation-reports-best-quarterly-results-since-2014-300355287.html	-0.020	1-Nov-16
956891401119203329	Happening now: TimkenSteel Q4 & full-year 2017 earnings call. Tim Timken: "The 4th qtr saw a **48% increase in shipments** year over year, despite heavier-than-usual maintenance activities. **Record productivity** for days we were in operations resulted in strong shipments in the qtr."	-0.027	26-Jan-18

Figure 1.
Time-series patterns of bot and human engagement in firm-initiated earnings tweets

The figure shows the proportion of firm-initiated earnings announcement tweets that received bot and human engagement over the period 2008–2022.

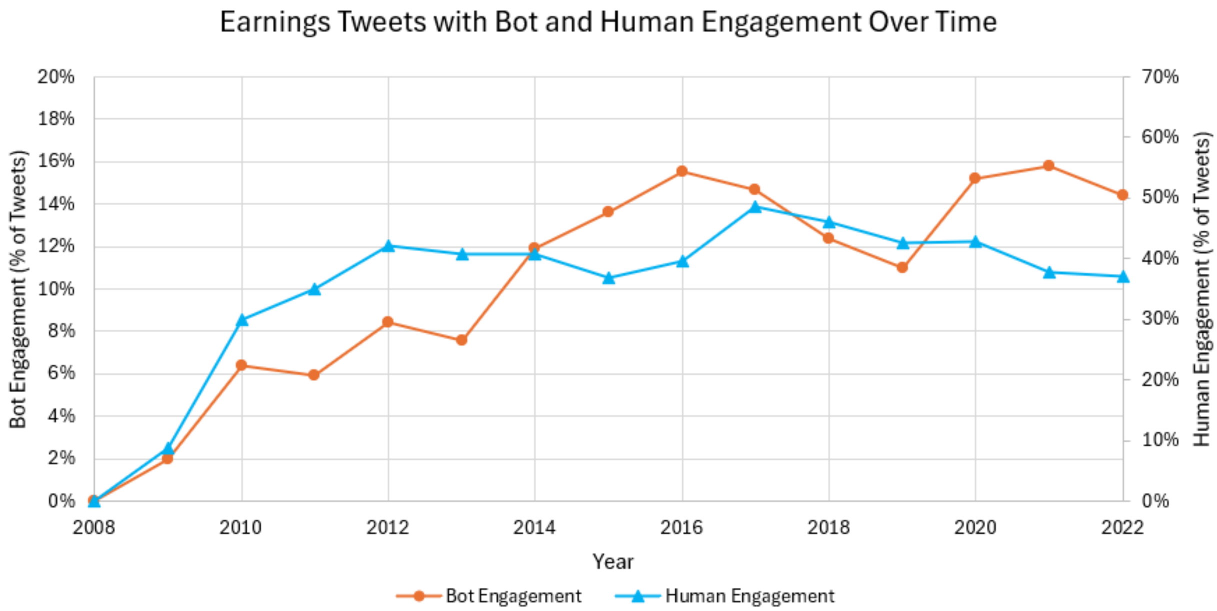


Table 1. Summary Statistics

This table reports summary statistics for the main variables used in the paper. Panel A presents the descriptive characteristics of the sample firms. Panel B reports the industry distribution of bot and human engagement in earnings announcement (EA) tweets. The sample comprises 8,779 firm-quarter observations over the 2008–2022 period. Detailed definitions of the variables are provided in Appendix A.

Panel A. Descriptive statistics

	Count	Mean	S. D	Min	P25	P50	P75	Max
CAR [0,2]	8,779	0.001	0.088	-0.280	-0.040	0.001	0.043	0.290
CAR [3,6]	8,779	0.002	0.050	-0.159	-0.021	0.000	0.023	0.189
Dum_isbot	8,779	0.126	0.332	0.000	0.000	0.000	0.000	1.000
Dum_onlyhuman	8,779	0.399	0.490	0.000	0.000	0.000	1.000	1.000
BotImpact	8,779	0.953	2.619	0.000	0.000	0.000	0.000	12.866
HumanImpact	8,779	4.011	4.238	0.000	0.000	0.000	8.043	14.908
RSUE	8,779	5.479	2.883	1.000	3.000	5.000	8.000	10.000
Logsize	8,779	5.789	2.623	0.000	4.397	6.346	7.733	10.301
BM	8,779	0.416	0.367	0.009	0.176	0.316	0.550	2.432
Lev	8,779	0.251	0.183	0.000	0.086	0.248	0.385	0.738
Tang	8,779	0.216	0.223	0.002	0.060	0.126	0.285	0.870
Q4	8,779	0.206	0.404	0.000	0.000	0.000	0.000	1.000
ROA	8,779	0.008	0.065	-0.250	0.006	0.026	0.040	0.111
logage	8,779	2.764	0.943	0.693	1.946	3.091	3.526	3.932
MOM	8,779	0.005	0.067	-0.202	-0.028	0.005	0.037	0.239
Stkvol	8,779	0.122	0.081	0.031	0.066	0.098	0.151	0.476
Sgct_sentiment_rank	8,779	-1.028	4.589	-9.000	-4.000	-1.000	3.000	9.000
Firmttage	8,779	1.959	0.527	0.693	1.609	2.079	2.398	2.708
Firm_Following	8,779	6.092	1.615	0.000	5.187	6.168	7.125	9.994
Firm_Followers	8,779	9.063	2.045	3.332	7.544	9.025	10.361	14.880
Num of hashtags (#)	8,779	0.608	1.159	0.000	0.000	0.000	1.000	14.000
Num of mentions (@)	8,779	0.185	0.571	0.000	0.000	0.000	0.000	15.000
Num of tickers ($)	8,779	0.273	0.450	0.000	0.000	0.000	1.000	3.000
Num of links	8,779	0.881	0.387	0.000	1.000	1.000	1.000	3.000
Num of words	8,779	11.471	5.509	0.000	7.000	10.000	14.000	32.000

Table 1, continued

Panel B. Industry Distribution of Bot and Human Engagement in EA Tweets

	Dum_isbot	Dum_onlyhuman	FF12 Industry
7	**0.233**	**0.488**	Telephone and Television Transmission
2	**0.222**	0.292	Consumer Durables -- Cars, TVs, Furniture, Household Appliances
4	**0.216**	0.316	Oil, Gas, and Coal Extraction and Products
3	0.145	0.363	Manufacturing -- Machinery, Trucks, Planes, Off Furn, Paper, Com Printing
6	0.142	0.400	Business Equipment -- Computers, Software, and Electronic Equipment
12	0.117	0.374	Other -- Mines, Constr, BldMt, Trans, Hotels, Bus Serv, Entertainment
10	0.115	0.425	Healthcare, Medical Equipment, and Drugs
1	0.099	**0.505**	Consumer Nondurables -- Food, Tobacco, Textiles, Apparel, Leather, Toys
8	0.094	0.349	Utilities
5	0.072	**0.493**	Chemicals and Allied Products
9	0.069	0.371	Wholesale, Retail, and Some Services (Laundries, Repair Shops)

Table 2. Univariate Analysis of Bot and Human Engagement in EA Tweets

This table presents univariate analysis of the firm-, tweet-, and account-specific characteristics for firms with and without bot engagement. ∗, ∗∗, ∗∗∗ denote significance of t -test on the mean difference at the 10%, 5%, and 1% level respectively.
The sample comprises 8,779 firm-quarter observations over the 2008–2022 period. Detailed definitions of the variables are provided in Appendix A.

	Mean		Diff
	Bot=0 (N=7,674)	Bot=1 (N=1,105)	
Logsize	5.715	6.303	-0.588***
BTM	0.422	0.369	0.053***
Lev	0.251	0.256	-0.005
RSUE	5.486	5.425	0.061
ROA	0.008	0.004	0.004**
Logage	2.763	2.778	-0.015
Tang	0.215	0.221	-0.006
Num of hashtags (#)	0.596	0.688	-0.092**
Num of mentions (@)	0.175	0.252	-0.076***
Num of tickers ($)	0.262	0.350	-0.088***
Num of links	0.886	0.846	0.040***
Num of words	11.425	11.785	-0.359**
Firmttage	1.931	2.150	-0.218***
Firm_Following	1.538	1.609	-0.072***
Firm_Followers	1.621	1.850	-0.229***
sugarcoat_sentiment_rank	-1.064	-0.777	-0.287*

Table 3. Bot Engagement and Return Patterns Around Earnings Tweets

This table reports regression results on the effect of bot engagement on return patterns around earnings announcement tweets. Panel A reports the full-sample regression results. Panel B reports regression results for subsamples based on positive and negative standardized unexpected earnings (SUE). The dependent variables are two measures of cumulative abnormal return (CAR) around the earnings tweet date. CAR [0,2] is defined as the cumulative abnormal return over the window from the earnings tweet day (day 0) to two days after the tweet (day 2). CAR [3,6] is defined as the cumulative abnormal return over the window from three days after the earnings tweet (day 3) to six days after the tweet (day 6). Abnormal returns are computed as the raw return minus the average return of all firms in the same size decile. The key independent variable is *BotImpact*, defined as the natural logarithm of one plus the total number of followers and followings of bot accounts that engage with a firm's tweet through a retweet, quote, or comment. Accounts with Botometer scores above 3.0 are classified as bot accounts. The sample comprises 8,779 firm-quarter observations over the 2008–2022 period. Industry and year-quarter fixed effects are included in each regression. The t-statistics reported in parentheses are based on standard errors clustered by firm. $*$, $**$, $***$ denote significance at the 10%, 5%, and 1% level respectively. Detailed definitions of the variables are provided in Appendix A.

Panel A. Full sample

	(1)	(2)	(3)	(4)	(5)	(6)
	Contemporaneous Window				Reversal Window	
	CAR [0,0]	CAR [0,0]	CAR [0,2]	CAR [0,2]	CAR [3,6]	CAR [3,6]
BotImpact	0.0005*	0.0007***	0.0007**	0.0010***	-0.0004**	-0.0004**
	(1.91)	(2.76)	(2.10)	(2.68)	(-2.16)	(-2.06)
RSUE		0.0058***		0.0071***		-0.0001
		(18.62)		(16.05)		(-0.58)
Logsize		-0.0018***		-0.0019**		-0.0001
		(-3.14)		(-2.36)		(-0.33)
Bm		-0.0015		-0.0023		0.0023
		(-0.58)		(-0.66)		(0.91)
Lev		0.0036		0.0007		-0.0064
		(0.77)		(0.11)		(-1.50)
Tang		-0.0028		-0.0029		-0.0009
		(-0.66)		(-0.48)		(-0.25)
Q4		0.0437**		0.0647***		-0.0402**
		(2.54)		(2.76)		(-2.21)
ROA		0.0508***		0.0636**		-0.0013
		(2.64)		(2.38)		(-0.08)
Logage		-0.0009		0.0011		0.0009
		(-0.93)		(0.78)		(1.05)
MOM		-0.3294*		-0.6286**		-0.4704***
		(-1.90)		(-2.45)		(-2.74)
Stkvol		-0.0030		0.0414*		0.0174
		(-0.20)		(1.94)		(1.17)
Logana		0.0019		0.0012		0.0009

		(1.40)		(0.64)		(0.87)
Observations	8779	8779	8779	8779	8779	8779
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.008	0.079	0.010	0.067	0.016	0.020

Table 3, continued

Panel B. Stock Returns Around the Tweet Date: Positive vs. Negative SUE Firms

	(1)	(2)	(3)	(4)
	Negative SUE Firms		Positive SUE Firms	
	CAR [0,2]	CAR [3,6]	CAR [0,2]	CAR [3,6]
BotImpact	0.0021**	-0.0009*	0.0005	-0.0003
	(2.52)	(-1.71)	(1.39)	(-1.48)
RSUE	0.0112***	-0.0020	0.0069***	0.0002
	(3.47)	(-0.94)	(11.96)	(0.72)
Logsize	-0.0038**	-0.0016	-0.0012	0.0005
	(-2.24)	(-1.59)	(-1.31)	(1.04)
Bm	-0.0023	0.0039	0.0008	-0.0000
	(-0.33)	(0.77)	(0.18)	(-0.00)
Lev	0.0157	0.0013	0.0005	-0.0101**
	(1.24)	(0.14)	(0.06)	(-2.23)
Tang	-0.0086	-0.0090	-0.0018	0.0023
	(-0.63)	(-1.07)	(-0.27)	(0.67)
Q4	-0.0465	-0.0207	0.0818***	-0.0410**
	(-0.90)	(-0.41)	(2.98)	(-2.12)
ROA	-0.0490	0.0428	0.1575***	-0.0153
	(-0.89)	(1.31)	(4.81)	(-0.76)
Logage	-0.0024	0.0031	0.0023	0.0001
	(-0.87)	(1.64)	(1.41)	(0.14)
MOM	-1.5559***	-0.4502	-0.1611	-0.4637**
	(-3.44)	(-1.32)	(-0.48)	(-2.39)
Stkvol	0.0092	0.0083	0.0737***	0.0206
	(0.26)	(0.31)	(2.62)	(1.13)
Logana	0.0019	0.0032	-0.0000	0.0002
	(0.44)	(1.31)	(-0.02)	(0.14)
Observations	2311	2311	6468	6468
Industry FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
R-squared	0.066	0.050	0.054	0.018

Table 4. Bot Engagement and Return Patterns: The Role of Sugarcoating

This table reports regression results on the effect of bot engagement on return patterns around earnings announcement tweets, conditional on firms' sugarcoating behavior. High- (low-) sugarcoat firms are defined as those with a sugarcoating measure (*sugarcoat_sentiment_rank*) above (below) the sample median within the same fiscal-year quarter. The variable *sugarcoat_sentiment_rank* is calculated as the difference between the decile rank of EA tweet sentiment and the decile rank of standardized unexpected earnings (SUE). Panel A reports the full-sample regression results. Panel B reports results for the subsample of firms with negative SUE, and Panel C reports results for the subsample of firms with positive SUE. The dependent variables are two measures of cumulative abnormal return (CAR) around the earnings tweet date. CAR [0,2] is defined as the cumulative abnormal return over the window from the earnings tweet day (day 0) to two days after the tweet (day 2). CAR [3,6] is defined as the cumulative abnormal return over the window from three days after the earnings tweet (day 3) to six days after the tweet (day 6). Abnormal returns are computed as the raw return minus the average return of all firms in the same size decile. The key independent variable is *BotImpact*, defined as the natural logarithm of one plus the total number of followers and followings of bot accounts that engage with a firm's tweet through a retweet, quote, or comment. Accounts with Botometer scores above 3.0 are classified as bot accounts. The sample comprises 8,779 firm-quarter observations over the 2008–2022 period. Industry and year-quarter fixed effects are included in each regression. The t-statistics reported in parentheses are based on standard errors clustered by firm. *, **, *** denote significance at the 10%, 5%, and 1% level respectively. Detailed definitions of the variables are provided in Appendix A.

Panel A. Full sample

	(1)	(2)	(3)	(4)
	High Sugarcoating Firms		Low Sugarcoating Firms	
	CAR [0,2]	CAR [3,6]	CAR [0,2]	CAR [3,6]
BotImpact	0.0016***	-0.0007**	0.0004	-0.0002
	(3.02)	(-2.20)	(0.71)	(-0.59)
RSUE	0.0086***	-0.0000	0.0066***	0.0002
	(13.28)	(-0.00)	(10.66)	(0.52)
Logsize	-0.0025**	-0.0000	-0.0019*	-0.0001
	(-2.10)	(-0.01)	(-1.70)	(-0.20)
Bm	-0.0131**	0.0053	0.0069	-0.0008
	(-2.47)	(1.42)	(1.34)	(-0.26)
Lev	-0.0084	-0.0011	0.0094	-0.0119**
	(-0.81)	(-0.17)	(1.01)	(-2.20)
Tang	-0.0104	0.0012	0.0006	-0.0001
	(-1.11)	(0.23)	(0.07)	(-0.02)
Q4	0.0567	-0.0236	-0.0462**	-0.0645***
	(1.55)	(-1.21)	(-2.54)	(-2.82)
ROA	-0.0716*	0.0201	0.1768***	-0.0235
	(-1.66)	(0.78)	(4.84)	(-1.11)
Logage	-0.0004	0.0003	0.0022	0.0013
	(-0.21)	(0.19)	(1.16)	(1.20)

MOM	-0.6328*	-0.6494**	-0.7346**	-0.3489
	(-1.70)	(-2.47)	(-2.00)	(-1.54)
Stkvol	0.0217	0.0323	0.0622**	0.0044
	(0.65)	(1.33)	(2.04)	(0.22)
Logana	0.0046*	-0.0006	-0.0010	0.0019
	(1.76)	(-0.36)	(-0.43)	(1.49)
Observations	3971	3971	4808	4808
Industry FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
R-squared	0.084	0.029	0.070	0.026

Table 4, continued

Panel B. Sugar-coating effect: Negative SUE Firms

	(1)	(2)	(3)	(4)
	High Sugarcoating Firms		Low Sugarcoating Firms	
	CAR [0,2]	CAR [3,6]	CAR [0,2]	CAR [3,6]
BotImpact	0.0039***	-0.0022**	0.0004	0.0000
	(2.66)	(-2.21)	(0.33)	(0.05)
RSUE	0.0088*	0.0007	0.0146***	-0.0040
	(1.78)	(0.22)	(3.35)	(-1.41)
Logsize	-0.0033	-0.0025	-0.0059**	-0.0010
	(-1.19)	(-1.36)	(-2.36)	(-0.85)
Bm	-0.0053	0.0056	0.0040	0.0038
	(-0.50)	(0.82)	(0.42)	(0.52)
Lev	-0.0130	0.0008	0.0378**	-0.0003
	(-0.63)	(0.06)	(2.43)	(-0.02)
Tang	-0.0052	-0.0090	-0.0063	-0.0121
	(-0.24)	(-0.68)	(-0.34)	(-1.16)
Q4	-0.0252	-0.0001	-0.0625	-0.0687
	(-0.94)	(-0.00)	(-0.80)	(-1.56)
ROA	-0.0385	0.0429	-0.0344	0.0470
	(-0.46)	(0.82)	(-0.47)	(1.11)
Logage	-0.0075*	0.0039	0.0025	0.0026
	(-1.67)	(1.32)	(0.72)	(1.03)
MOM	-1.4335**	-0.5086	-1.9705***	-0.3353
	(-2.34)	(-1.06)	(-2.81)	(-0.70)
Stkvol	-0.0017	0.0197	0.0159	0.0027
	(-0.03)	(0.49)	(0.32)	(0.07)
Logana	0.0021	0.0032	0.0033	0.0032
	(0.35)	(0.75)	(0.58)	(1.04)
Observations	1097	1097	1214	1214
Industry FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
R-squared	0.102	0.077	0.093	0.070

Table 4, continued

Panel C. Sugar-coating effect: Positive SUE Firms

	(1)	(2)	(3)	(4)
	High Sugarcoating Firms		Low Sugarcoating Firms	
	CAR [0,2]	CAR [3,6]	CAR [0,2]	CAR [3,6]
BotImpact	0.0006	-0.0003	0.0004	-0.0003
	(1.25)	(-1.10)	(0.69)	(-0.89)
RSUE	0.0074***	0.0005	0.0067***	-0.0003
	(9.45)	(1.22)	(7.91)	(-0.58)
Logsize	-0.0014	0.0016**	-0.0011	-0.0004
	(-1.07)	(2.16)	(-0.93)	(-0.53)
Bm	-0.0077	0.0027	0.0063	-0.0022
	(-1.27)	(0.68)	(1.05)	(-0.55)
Lev	-0.0045	-0.0122*	0.0023	-0.0091
	(-0.41)	(-1.83)	(0.22)	(-1.54)
Tang	-0.0167*	0.0051	0.0101	0.0031
	(-1.70)	(0.87)	(1.15)	(0.57)
Q4	0.0373**	0.0108	0.0279	-0.0565***
	(1.99)	(1.06)	(0.50)	(-3.04)
ROA	0.0854*	0.0154	0.2067***	-0.0416
	(1.81)	(0.51)	(4.45)	(-1.61)
Logage	0.0022	-0.0014	0.0029	0.0013
	(0.96)	(-1.07)	(1.27)	(0.92)
MOM	0.0073	-0.3582	-0.3074	-0.5482**
	(0.02)	(-1.37)	(-0.67)	(-2.04)
Stkvol	0.0526	0.0199	0.0907**	0.0205
	(1.34)	(0.76)	(2.26)	(0.80)
Logana	0.0020	-0.0035**	-0.0013	0.0027*
	(0.71)	(-2.26)	(-0.48)	(1.80)
Observations	3140	3140	3328	3328
Industry FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
R-squared	0.064	0.028	0.062	0.031

Table 5. Daily Investor Trading Responses to Bot Engagement Around Earnings Announcement Tweets

This table reports regression results on the effect of bot engagement on retail trading behavior around earnings announcement tweets over the window from day 0 to day 6. The dependent variable is *Retail_BuySell_Imbalance*, defined as the difference between the number of retail buy and sell trades on day *t* relative to the release of an earnings announcement tweet, scaled by their sum. Retail trades are identified using the methodology developed by Boehmer et al. (2021), and trade direction (buy or sell) is classified following the quote midpoint-based algorithm proposed by Barber et al. (2024). The key independent variable is *BotImpact*, defined as the natural logarithm of one plus the total number of followers and followings of bot accounts that engage with a firm's tweet through a retweet, quote, or comment. Accounts with Botometer scores above 3.0 are classified as bot accounts. Industry and year-quarter fixed effects are included in each regression. The t-statistics reported in parentheses are based on standard errors clustered by firm. $*$, $**$, $***$ denote significance at the 10%, 5%, and 1% level respectively. Detailed definitions of the variables are provided in Appendix A.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Retail_BuySell_Imbalance						
	Day 0	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6
BotImpact	0.0029***	0.0034***	0.0027***	0.0036***	0.0025***	0.0029***	0.0027***
	(3.87)	(4.47)	(3.13)	(4.55)	(3.08)	(3.45)	(3.12)
RSUE	-0.0017**	0.0000	-0.0021**	-0.0016*	-0.0001	-0.0005	0.0000
	(-2.14)	(0.05)	(-2.43)	(-1.74)	(-0.07)	(-0.46)	(0.03)
Logsize	0.0043**	-0.0005	0.0062***	0.0023	-0.0018	-0.0002	-0.0007
	(2.19)	(-0.23)	(2.75)	(1.15)	(-0.81)	(-0.06)	(-0.32)
Bm	-0.0220***	-0.0224***	-0.0345***	-0.0203**	-0.0269***	-0.0311***	-0.0391***
	(-3.09)	(-2.68)	(-4.60)	(-2.35)	(-3.27)	(-3.72)	(-4.37)
Lev	-0.0288**	-0.0166	-0.0180	-0.0175	-0.0040	-0.0055	0.0079
	(-1.99)	(-1.04)	(-1.17)	(-1.09)	(-0.25)	(-0.32)	(0.49)
Tang	0.0160	-0.0033	0.0121	0.0188	0.0033	0.0060	0.0126
	(1.15)	(-0.20)	(0.67)	(1.25)	(0.20)	(0.38)	(0.74)
Q4	0.0324	0.1065	0.1593	0.0108	-0.2405**	0.2067	0.1140
	(0.22)	(0.82)	(1.54)	(0.45)	(-2.15)	(1.51)	(0.45)
ROA	-0.0522	-0.0618	-0.1005	-0.0541	0.0116	-0.0547	-0.0078
	(-0.95)	(-1.00)	(-1.56)	(-0.84)	(0.17)	(-0.82)	(-0.12)
Logage	-0.0003	0.0041	0.0045	0.0037	0.0018	0.0048	0.0048

	(-0.08)	(1.04)	(1.25)	(0.99)	(0.44)	(1.24)	(1.15)
MOM	-0.0472	0.3002	0.5563	0.2165	0.9192*	0.5529	-0.0063
	(-0.11)	(0.66)	(1.16)	(0.45)	(1.75)	(1.02)	(-0.01)
Stkvol	0.1409***	0.0226	0.1564***	0.1209***	0.0973**	0.1051**	0.0751
	(3.51)	(0.53)	(3.39)	(2.75)	(2.17)	(2.36)	(1.62)
Logana	0.0065*	0.0157***	0.0113***	0.0072	0.0084*	0.0105**	0.0068
	(1.77)	(3.56)	(2.65)	(1.62)	(1.91)	(2.29)	(1.45)
Observations	8503	8379	8290	8368	8363	8430	8364
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.037	0.028	0.036	0.025	0.024	0.027	0.027

Table 6. Intraday Retail Trading Responses to Bot Engagement Around Earnings Announcement Tweets

This table reports regression results on the effect of bot engagement on retail trading behavior around earnings announcement (EA) tweets during intraday minutes surrounding the release of the EA tweet. The dependent variable is the difference between the number of retail buy and sell trades over the intraday window from *m* to *n* minutes relative to the EA tweet, scaled by their sum. Retail trades are identified using the methodology of Boehmer et al. (2021), and trade direction (buy versus sell) is classified following the quote midpoint–based algorithm of Barber et al. (2024). The key independent variable is *BotImpact*, defined as the natural logarithm of one plus the total number of followers and followings of bot accounts that engage with a firm's tweet through a retweet, quote, or comment. Accounts with Botometer scores above 3.0 are classified as bot accounts. Industry and year-quarter fixed effects are included in each regression. The t-statistics reported in parentheses are based on standard errors clustered by firm. $*$, $**$, $***$ denote significance at the 10%, 5%, and 1% level respectively. Detailed definitions of the variables are provided in Appendix A.

	(1)	(2)	(3)	(4)	(5)
			Retail_BuySell_Imbalance		
	[0, 45] min	[45, 90] min	[90, 135] min	[135, 180] min	[180, 225] min
BotImpact	0.0029**	0.0046***	0.0038***	0.0030**	0.0019
	(2.36)	(3.39)	(2.87)	(2.21)	(1.24)
RSUE	0.0015	-0.0031**	-0.0015	-0.0026	-0.0020
	(1.05)	(-2.03)	(-0.93)	(-1.59)	(-1.14)
Logsize	0.0063**	0.0054	-0.0013	0.0043	0.0011
	(1.99)	(1.58)	(-0.40)	(1.22)	(0.32)
Bm	-0.0137	-0.0162	-0.0176	-0.0263*	-0.0222
	(-1.05)	(-1.03)	(-1.22)	(-1.71)	(-1.27)
Lev	0.0133	-0.0519**	-0.0227	-0.0316	-0.0359
	(0.56)	(-2.12)	(-0.85)	(-1.17)	(-1.36)
Tang	0.0352	0.0389	0.0264	0.0144	-0.0478
	(1.37)	(1.56)	(1.02)	(0.53)	(-1.64)
Q4	-0.0660	0.1869*	0.1038*	0.4403***	-0.1988
	(-0.43)	(1.70)	(1.70)	(6.60)	(-0.88)
ROA	-0.0705	-0.0402	-0.0906	-0.0121	0.0412
	(-0.68)	(-0.40)	(-0.81)	(-0.10)	(0.36)
Logage	-0.0041	0.0032	0.0000	0.0054	0.0056
	(-0.75)	(0.54)	(0.01)	(0.91)	(0.91)

MOM	-0.1564	-0.5109	0.7440	0.0082	2.1989**
	(-0.20)	(-0.63)	(0.86)	(0.01)	(2.38)
Stkvol	0.1017	0.1321*	0.0212	0.2787***	0.1524*
	(1.33)	(1.71)	(0.31)	(3.11)	(1.81)
Observations	8387	8171	7875	7663	7432
Industry FE	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes
R-squared	0.018	0.019	0.018	0.020	0.017

Table 7. Robustness Check

This table presents estimates from difference-in-differences regressions exploiting a platform-wide disruption in Twitter's bot activity policies during the first quarter of 2019 as an exogenous shock to bot dissemination. *Post* equals one if the earnings announcement (EA) tweet occurs after the first quarter of 2019 and zero otherwise. *Treat* is an indicator equal to one for firms with above-median bot exposure prior to the 2019Q1 shock and zero otherwise. Bot exposure is measured as the firm's average number of interactions, including quotes, retweets, and replies, per EA tweet before 2018. Each tweet's engagement is weighted by the firm's frequency of EA tweets during the pre-period to reflect persistent dissemination activity. The dependent variable, $\Delta CAR = CAR\ [0,2] - CAR\ [0,6]$, captures the degree of short-term return reversal following the EA tweet. Columns (1)–(2) report results for the sample period 2018Q2–2020Q1; columns (3)–(4) for 2018Q1–2020Q2; and columns (5)–(6) for 2017Q4–2020Q3. Industry and year-quarter fixed effects are included in each regression. The t-statistics reported in parentheses are based on standard errors clustered by firm. $*$, $**$, $***$ denote significance at the 10%, 5%, and 1% level respectively. Detailed definitions of the variables are provided in Appendix A.

	(1) ΔCAR	(2) ΔCAR	(3) ΔCAR	(4) ΔCAR	(5) ΔCAR	(6) ΔCAR
Treat	0.0059*	0.0040	0.0030	0.0015	0.0032	0.0020
	(1.78)	(1.16)	(0.99)	(0.47)	(1.19)	(0.72)
Post	0.0025	0.0046	0.0049	0.0069	0.0081	0.0092
	(0.39)	(0.72)	(0.88)	(1.14)	(1.39)	(1.48)
Treat*Post	-0.0104**	-0.0104**	-0.0107**	-0.0104**	-0.0112***	-0.0111***
	(-2.00)	(-1.98)	(-2.40)	(-2.33)	(-2.81)	(-2.73)
RSUE		0.0008		0.0009*		0.0006
		(1.32)		(1.72)		(1.24)
Logsize		0.0015		0.0008		0.0008
		(1.19)		(0.75)		(0.82)
Bm		-0.0068		-0.0021		-0.0011
		(-1.27)		(-0.45)		(-0.25)
Lev		0.0041		0.0012		0.0087
		(0.47)		(0.16)		(1.26)
Tang		-0.0016		-0.0023		0.0003
		(-0.18)		(-0.31)		(0.04)
Q4		-0.0089		-0.0082		-0.0108
		(-1.13)		(-1.10)		(-1.54)
ROA		-0.0272		-0.0136		-0.0131
		(-0.68)		(-0.36)		(-0.40)
Logage		-0.0055**		-0.0048**		-0.0034*
		(-2.31)		(-2.57)		(-1.90)
MOM		-0.1972		0.2035		0.1453
		(-0.41)		(0.52)		(0.42)
Stkvol		-0.0042		-0.0516**		-0.0249
		(-0.13)		(-2.00)		(-1.07)
Logana		-0.0003		0.0005		0.0011

		(-0.13)		(0.20)		(0.57)
Observations	1212	1212	1560	1560	1877	1877
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.027	0.038	0.025	0.037	0.024	0.031

Table 8. Additional Analysis

This table reports regression results on the effect of bot engagement on return patterns around earnings announcement tweets, conditional on firms' retail attention and information transparency. Panel A reports subsample regression results based on proxies for retail attention, measured by Twitter visibility and stock price volatility. High- (low-) Twitter visibility firms are defined as those with the number of followers and followings on the firm's official Twitter account above (below) the sample median within the same fiscal-year quarter. High- (low-) stock price volatility firms are defined as those with a standard deviation of monthly stock prices in the past year above (below) the sample median within the same fiscal-year quarter. Panel B reports subsample regression results based on proxies for information transparency, measured by earnings quality and firm size. High- (low-) EM firms are defined as those with earnings management below (above) the sample median within the same fiscal-year quarter. Earnings management is measured as the sum of the decile rank of discretionary accruals and the decile rank of real earnings management. Discretionary accruals are estimated following Dechow et al. (1995), and real earnings management is measured following Roychowdhury (2006). Small (large) firms are defined as those with the natural logarithm of total assets below (above) the sample median within the same fiscal-year quarter. The key independent variable is *BotImpact*, defined as the natural logarithm of one plus the total number of followers and followings of bot accounts that engage with a firm's tweet through a retweet, quote, or comment. Accounts with Botometer scores above 3.0 are classified as bot accounts. The sample comprises 8,779 firm-quarter observations over the 2008–2022 period. Industry and year-quarter fixed effects are included in each regression. The t-statistics reported in parentheses are based on standard errors clustered by firm. *, **, *** denote significance at the 10%, 5%, and 1% level respectively. Detailed definitions of the variables are provided in Appendix A.

Panel A. Retail Attention: Firm Twitter Visibility and Stock Price Volatility

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Firms with High Twitter Visibility		Firms with Low Twitter Visibility		Firms with High Stock Price Volatility		Firms with Low Stock Price Volatility	
	CAR [0,2]	CAR [3,6]	CAR [0,2]	CAR [3,6]	CAR [0,2]	CAR [3,6]	CAR [0,2]	CAR [3,6]
BotImpact	0.0015***	-0.0010***	0.0003	0.0001	0.0020***	-0.0008**	0.0000	-0.0001
	(3.14)	(-3.19)	(0.52)	(0.46)	(2.95)	(-1.97)	(0.02)	(-0.67)
RSUE	0.0068***	0.0001	0.0076***	-0.0003	0.0075***	-0.0001	0.0065***	-0.0003
	(10.74)	(0.16)	(13.09)	(-1.08)	(s12.46)	(-0.23)	(13.33)	(-1.19)
Logsize	-0.0015	-0.0001	-0.0021*	-0.0002	-0.0025*	-0.0002	-0.0018*	0.0000
	(-1.45)	(-0.17)	(-1.76)	(-0.29)	(-1.90)	(-0.28)	(-1.96)	(0.00)
Bm	0.0055	-0.0000	-0.0082	0.0045	0.0030	0.0016	-0.0137***	0.0019
	(1.23)	(-0.01)	(-1.58)	(1.28)	(0.63)	(0.51)	(-2.85)	(0.56)

Lev	0.0103	-0.0052	-0.0041	-0.0082	0.0005	-0.0086	0.0002	-0.0045
	(1.05)	(-0.93)	(-0.48)	(-1.30)	(0.05)	(-1.25)	(0.02)	(-1.11)
Tang	-0.0041	0.0006	-0.0026	-0.0019	-0.0133	0.0002	0.0045	-0.0011
	(-0.39)	(0.09)	(-0.36)	(-0.43)	(-1.32)	(0.03)	(0.67)	(-0.38)
Q4	0.0351	-0.0503***	0.0890***	-0.0313***	-0.0093	-0.0093	-0.0271	-0.0831***
	(1.02)	(-4.91)	(2.74)	(-2.88)	(-0.24)	(-0.24)	(-1.61)	(-3.79)
ROA	0.0409	-0.0066	0.1087**	0.0103	0.0726**	-0.0038	0.0480	-0.0010
	(1.13)	(-0.32)	(2.46)	(0.38)	(2.00)	(-0.17)	(0.94)	(-0.03)
Logage	0.0006	0.0006	0.0033	0.0006	0.0006	0.0010	0.0014	0.0004
	(0.32)	(0.53)	(1.58)	(0.45)	(0.29)	(0.80)	(0.78)	(0.41)
MOM	-0.9812***	-0.5923**	-0.2556	-0.2782	-0.9452***	-0.5888***	-0.0497	-0.0882
	(-2.68)	(-2.25)	(-0.68)	(-1.29)	(-3.06)	(-2.87)	(-0.12)	(-0.31)
Stkvol	0.0577**	0.0273	0.0029	0.0061	0.0487*	0.0208	-0.0579	0.0122
	(2.20)	(1.40)	(0.08)	(0.28)	(1.68)	(1.08)	(-1.04)	(0.35)
Logana	-0.0006	0.0020	0.0018	-0.0001	0.0020	0.0026	0.0011	-0.0011
	(-0.21)	(1.25)	(0.71)	(-0.08)	(0.69)	(1.58)	(0.55)	(-1.03)
Observations	4373	4373	4406	4406	4374	4374	4405	4405
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.075	0.035	0.086	0.020	0.079	0.033	0.085	0.029

Table 8, continued

Panel B. Information Transparency: Earnings Quality and Firm Size

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	High EM Firms		Low EM Firms		Small Firms		Large Firms	
	CAR [0,2]	CAR [3,6]	CAR [0,2]	CAR [3,6]	CAR [0,2]	CAR [3,6]	CAR [0,2]	CAR [3,6]
BotImpact	0.0015**	-0.0009**	0.0004	-0.0001	0.0017**	-0.0011**	0.0002	-0.0001
	(2.48)	(-2.31)	(0.80)	(-0.26)	(2.13)	(-2.36)	(0.70)	(-0.30)
Humanimpact	0.0006	-0.0000	0.0004	-0.0000	0.0007*	0.0003	0.0002	-0.0002
	(1.57)	(-0.00)	(1.19)	(-0.21)	(1.80)	(1.28)	(0.95)	(-1.29)
RSUE	0.0065***	-0.0001	0.0077***	-0.0002	0.0071***	-0.0002	0.0069***	0.0001
	(10.88)	(-0.28)	(12.93)	(-0.53)	(12.32)	(-0.73)	(12.10)	(0.49)
Logsize	-0.0022*	-0.0001	-0.0020*	-0.0001	-0.0031**	0.0008	-0.0005	-0.0002
	(-1.75)	(-0.15)	(-1.74)	(-0.13)	(-2.10)	(0.99)	(-0.45)	(-0.28)
Bm	-0.0026	0.0034	-0.0014	0.0004	-0.0000	0.0010	-0.0076*	0.0032
	(-0.43)	(0.89)	(-0.30)	(0.10)	(-0.00)	(0.30)	(-1.69)	(0.87)
Lev	0.0134	-0.0104*	-0.0111	-0.0016	0.0072	-0.0099	-0.0049	-0.0006
	(1.43)	(-1.79)	(-1.15)	(-0.27)	(0.69)	(-1.51)	(-0.62)	(-0.12)
Tang	0.0033	0.0023	-0.0040	-0.0035	-0.0168	-0.0028	0.0108*	0.0013
	(0.28)	(0.36)	(-0.51)	(-0.77)	(-1.62)	(-0.44)	(1.71)	(0.32)
Q4	-0.0264	-0.0679**	0.0552*	-0.0616***	0.0234	-0.0142	-0.0116	-0.0863***
	(-0.91)	(-2.47)	(1.81)	(-6.25)	(0.67)	(-1.09)	(-0.76)	(-3.28)
ROA	0.0814**	-0.0074	0.0488	0.0107	0.1112***	0.0080	-0.0327	-0.0730**
	(2.16)	(-0.35)	(0.94)	(0.34)	(3.03)	(0.38)	(-0.61)	(-2.20)
Logage	0.0004	0.0002	0.0029	0.0015	0.0020	0.0020*	-0.0000	-0.0001
	(0.18)	(0.14)	(1.59)	(1.41)	(0.98)	(1.72)	(-0.02)	(-0.07)
MOM	-0.9753***	-0.5769**	-0.4678	-0.3084	-0.8638***	-0.5242**	-0.1740	-0.4321*
	(-2.61)	(-2.51)	(-1.27)	(-1.12)	(-2.67)	(-2.35)	(-0.44)	(-1.78)
Stkvol	0.0539*	-0.0058	0.0155	0.0647***	0.0556**	0.0236	-0.0021	-0.0029
	(1.92)	(-0.29)	(0.42)	(2.66)	(2.10)	(1.35)	(-0.06)	(-0.11)
Logana	0.0002	0.0008	0.0009	0.0006	0.0008	0.0001	0.0008	0.0022*
	(0.06)	(0.48)	(0.41)	(0.46)	(0.27)	(0.07)	(0.38)	(1.76)
Observations	3933	3933	4516	4516	4409	4409	4370	4370

Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.069	0.031	0.085	0.027	0.078	0.032	0.070	0.024

Table 9. Relative Effects of Bot and Human Engagement in Earnings Announcement Tweets on Market Reactions

This table reports regression results on the effect of human and bot engagement on return patterns around earnings announcement tweets. Panel A reports the full-sample regression results. Panel B reports regression results for subsamples based on positive and negative standardized unexpected earnings (SUE). Panel C reports regression results for subsamples based on sugarcoating intensity.The dependent variables are two measures of cumulative abnormal return (CAR) around the earnings tweet date. CAR [0,2] is defined as the cumulative abnormal return over the window from the earnings tweet day (day 0) to two days after the tweet (day 2). CAR [3,6] is defined as the cumulative abnormal return over the window from three days after the earnings tweet (day 3) to six days after the tweet (day 6). Abnormal returns are computed as the raw return minus the average return of all firms in the same size decile. The key independent variable is *HumanImpact*, defined as Natural logarithm of one plus the total number of followers and followings of human accounts that engage with a firm's tweet through a retweet, quote, or comment. Accounts with Botometer scores lower than 3.0 are classified as human accounts. The sample comprises 8,779 firm-quarter observations over the 2008–2022 period. Industry and year-quarter fixed effects are included in each regression. The t-statistics reported in parentheses are based on standard errors clustered by firm. ∗, ∗∗, ∗∗∗ denote significance at the 10%, 5%, and 1% level respectively. Detailed definitions of the variables are provided in Appendix A.

Panel A. Full sample

	(1)	(2)	(3)	(4)	(5)	(6)
	Contemporaneous Window				Reversal Window	
	CAR [0,0]	CAR [0,0]	CAR [0,2]	CAR [0,2]	CAR [3,6]	CAR [3,6]
BotImpact		0.0005^{**}		0.0008^{**}		-0.0004^{**}
		(2.10)		(2.08)		(-2.08)
Humanimpact	0.0005^{***}	0.0004^{**}	0.0006^{***}	0.0005^{**}	-0.0001	0.0000
	(2.86)	(2.27)	(2.81)	(2.25)	(-0.44)	(0.05)
RSUE	0.0058^{***}	0.0058^{***}	0.0071^{***}	0.0071^{***}	-0.0001	-0.0001
	(18.63)	(18.61)	(16.07)	(16.05)	(-0.58)	(-0.58)
Logsize	-0.0019^{***}	-0.0020^{***}	-0.0020^{**}	-0.0022^{***}	-0.0002	-0.0001
	(-3.26)	(-3.41)	(-2.52)	(-2.66)	(-0.52)	(-0.33)
Bm	-0.0012	-0.0011	-0.0020	-0.0018	0.0024	0.0023
	(-0.48)	(-0.42)	(-0.56)	(-0.50)	(0.96)	(0.91)
Lev	0.0039	0.0042	0.0012	0.0016	-0.0061	-0.0064
	(0.83)	(0.90)	(0.18)	(0.25)	(-1.43)	(-1.49)
Tang	-0.0023	-0.0025	-0.0022	-0.0025	-0.0011	-0.0009
	(-0.54)	(-0.59)	(-0.37)	(-0.42)	(-0.30)	(-0.25)
Q4	0.0430^{**}	0.0422^{**}	0.0638^{***}	0.0626^{***}	-0.0409^{**}	-0.0402^{**}
	(2.49)	(2.45)	(2.71)	(2.66)	(-2.25)	(-2.21)
ROA	0.0517^{***}	0.0541^{***}	0.0647^{**}	0.0682^{**}	0.0007	-0.0013
	(2.66)	(2.80)	(2.42)	(2.54)	(0.05)	(-0.08)
Logage	-0.0009	-0.0008	0.0012	0.0012	0.0009	0.0009
	(-0.86)	(-0.85)	(0.84)	(0.86)	(1.07)	(1.06)
MOM	-0.3364^{*}	-0.3363^{*}	-0.6386^{**}	-0.6384^{**}	-0.4704^{***}	-0.4705^{***}

	(-1.94)	(-1.94)	(-2.49)	(-2.49)	(-2.74)	(-2.74)
Stkvol	-0.0031	-0.0042	0.0413*	0.0397*	0.0165	0.0174
	(-0.21)	(-0.29)	(1.93)	(1.86)	(1.11)	(1.17)
Logana	0.0018	0.0017	0.0010	0.0010	0.0008	0.0009
	(1.33)	(1.30)	(0.57)	(0.54)	(0.83)	(0.86)
Observations	8779	8779	8779	8779	8779	8779
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.079	0.079	0.067	0.068	0.019	0.020

Table 9, continued

Panel B. Subsamples by the Sign of Unexpected Earnings

	(1)	(2)	(3)	(4)
	Negative SUE Firms		Positive SUE Firms	
	CAR [0,2]	CAR [3,6]	CAR [0,2]	CAR [3,6]
BotImpact	0.0019**	-0.0011*	0.0003	-0.0003
	(2.28)	(-1.90)	(0.89)	(-1.29)
Humanimpact	0.0004	0.0003	0.0005**	-0.0001
	(0.75)	(0.78)	(1.99)	(-0.60)
RSUE	0.0112***	-0.0020	0.0069***	0.0002
	(3.46)	(-0.93)	(11.96)	(0.72)
Logsize	-0.0039**	-0.0017*	-0.0015	0.0006
	(-2.29)	(-1.66)	(-1.62)	(1.13)
Bm	-0.0021	0.0041	0.0014	-0.0001
	(-0.30)	(0.80)	(0.34)	(-0.04)
Lev	0.0165	0.0018	0.0013	-0.0102**
	(1.29)	(0.20)	(0.16)	(-2.25)
Tang	-0.0087	-0.0091	-0.0012	0.0022
	(-0.63)	(-1.08)	(-0.19)	(0.63)
Q4	-0.0464	-0.0206	0.0795***	-0.0406**
	(-0.90)	(-0.41)	(2.89)	(-2.11)
ROA	-0.0462	0.0446	0.1624***	-0.0161
	(-0.84)	(1.36)	(4.90)	(-0.80)
Logage	-0.0024	0.0031*	0.0025	0.0001
	(-0.86)	(1.66)	(1.49)	(0.12)
MOM	-1.5697***	-0.4591	-0.1658	-0.4628**
	(-3.48)	(-1.35)	(-0.50)	(-2.39)
Stkvol	0.0081	0.0076	0.0718**	0.0209
	(0.23)	(0.28)	(2.56)	(1.15)
Logana	0.0016	0.0031	-0.0002	0.0002
	(0.39)	(1.24)	(-0.09)	(0.17)
Observations	2311	2311	6468	6468
Industry FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
R-squared	0.066	0.050	0.054	0.019

Table 9, continued

Panel C. Subsamples by Sugarcoating Intensity

	(1)	(2)	(3)	(4)
	High Sugarcoating Firms		Low Sugarcoating Firms	
	CAR [0,2]	CAR [3,6]	CAR [0,2]	CAR [3,6]
BotImpact	0.0015***	-0.0007**	0.0001	-0.0001
	(2.86)	(-2.40)	(0.20)	(-0.46)
Humanimpact	0.0002	0.0002	0.0007**	-0.0001
	(0.71)	(0.79)	(2.03)	(-0.56)
RSUE	0.0086***	-0.0000	0.0066***	0.0002
	(13.28)	(-0.01)	(10.66)	(0.52)
Logsize	-0.0026**	-0.0001	-0.0022**	-0.0001
	(-2.17)	(-0.12)	(-1.99)	(-0.09)
Bm	-0.0129**	0.0055	0.0077	-0.0009
	(-2.41)	(1.45)	(1.47)	(-0.29)
Lev	-0.0079	-0.0007	0.0103	-0.0121**
	(-0.77)	(-0.11)	(1.11)	(-2.22)
Tang	-0.0102	0.0013	0.0013	-0.0002
	(-1.10)	(0.24)	(0.16)	(-0.05)
Q4	0.0557	-0.0243	0.0677*	-0.0341
	(1.52)	(-1.23)	(1.76)	(-1.62)
ROA	-0.0693	0.0217	0.1822***	-0.0244
	(-1.61)	(0.84)	(4.93)	(-1.14)
Logage	-0.0004	0.0003	0.0023	0.0013
	(-0.18)	(0.22)	(1.22)	(1.19)
MOM	-0.6384*	-0.6532**	-0.7465**	-0.3471
	(-1.72)	(-2.48)	(-2.03)	(-1.54)
Stkvol	0.0214	0.0321	0.0590*	0.0049
	(0.64)	(1.32)	(1.95)	(0.25)
Logana	0.0045*	-0.0007	-0.0012	0.0020
	(1.71)	(-0.40)	(-0.52)	(1.51)
Observations	3971	3971	4808	4808
Industry FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
R-squared	0.084	0.030	0.071	0.026

Table 10. Tendency To Correct Original Tweet Sentiment

This table reports results on the role of bot versus human accounts in sentiment correction. Panel A presents a univariate analysis of account-specific characteristics for bot and human accounts. Panel B reports regression results on the likelihood that users correct the sentiment of firm-initiated earnings announcement tweets at the tweet–user level. The dependent variable, *Correction*, is an indicator equal to one if a user's quote or comment on a firm tweet expresses more negative sentiment than the original tweet, conditional on the tweet being favorably framed. The variable equals zero for direct retweets without additional text or when the user's sentiment is not more negative than the firm's original message. The key independent variable is *IsBot*, an indicator equal to one if the user is classified as a bot account and zero otherwise. Industry and year-quarter fixed effects are included in each regression. The t-statistics reported in parentheses are based on standard errors clustered by firm. ∗, ∗∗, ∗∗∗ denote significance at the 10%, 5%, and 1% level respectively. Detailed definitions of the variables are provided in Appendix A.

Panel A. Univariate Analysis of Bot and Human Account

	Mean		Diff
	Human Account (N=13,554)	Bot Account (N=1,561)	
Number of Followers	2762.071	3871.949	-1109.878***
Number of Followings	1224.738	1655.225	-430.487***
Account age	13.304	11.995	1.309***

Panel B. User-tweet Level Analysis

	(1) Correction	(2) Correction
IsBot	-0.0116*	-0.0132**
	(-1.71)	(-2.03)
RSUE		-0.0063***
		(-7.14)
Logsize		0.0037**
		(2.05)
Bm		0.0083
		(0.82)
Lev		-0.0023
		(-0.16)
Tang		0.0395**
		(2.19)
Q4		0.0103
		(1.52)
ROA		-0.1319**
		(-2.35)
Logage		-0.0023
		(-0.59)

MOM		1.7327^{***}
		(3.07)
Stkvol		-0.0214
		(-0.45)
Logana		0.0092^{*}
		(1.70)
Observations	15,115	15,115
Industry FE	Yes	Yes
Year-Quarter FE	Yes	Yes
R-squared	0.026	0.037

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