Social Media Toxicity and Capital Markets

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ABSTRACT

This paper examines the existence, drivers, and implications of toxic content in financial social media. Using state-of-the-art machine learning algorithms to measure toxicity on Seeking Alpha, we find persistent toxicity primarily in the comments rather than articles, with over 50% of firms on the platform experiencing toxicity in recent years. Comment toxicity is greater for firms with more investor attention and disagreement, and for those led by female CEOs. We find three key results. First, toxicity displays a feedback loop in platform participation: past toxicity predicts more future toxic contributors for a given firm. Second, firms receiving more toxic comments have greater retail trading volume but less informative retail trades. Third, toxicity is associated with slower price discovery around earnings announcements, indicating potential broader market efficiency implications. Our findings suggest financial social media toxicity influences both user behavior and market outcomes, raising important considerations for platform governance in financial markets.

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1. Introduction

Social media platforms have transformed information flow in financial markets by providing easy access to investment analysis and fostering dialogue between market participants. These platforms enable rapid dissemination of financial insights through crowdsourced opinions, which research finds are informative and can reduce bias (e.g., Chen et al., 2014; Jame et al., 2022). However, the features that enable information sharing—open access, minimal oversight, and real-time interaction— can also foster toxic discourse: rude, disrespectful, or unreasonable comments, including harassment, offensive language, and hate speech. Studies document toxic discourse in non-financial platforms (e.g., Vogels, 2021; Wu 2018, 2020), but its presence in financial social media and its relation with financial information processing remains largely unexplored. The potential for toxicity impeding information processing contrasts with the platforms' informativeness for financial markets. Motivated by this tension, we explore the existence, drivers, and outcomes associated with toxic discourse in financial social media.

Understanding toxic content in financial social media is important for several reasons. First, unlike traditional media or analyst research, social media platforms rely heavily on user engagement to generate content. If toxic behavior discourages knowledgeable investor participation, the quality of crowdsourced investment opinions could decline. Second, social media's informal communication style makes it particularly susceptible to toxic interactions compared to conventional financial channels. Toxicity's potential to distract investors, disrupt their cognitive processing, and increase their information processing costs could undermine social media's primary benefits – democratized and timely investment information – by compromising investor decision-making and market efficiency. Third, the real-time nature of social media interactions amplifies the potential harm of toxic content. Toxicity can spread quickly, potentially impairing investor processing and trading decisions before moderators can intervene.

We examine toxicity in financial social media using articles and comments on Seeking Alpha (hereafter, SA), one of the most popular investment-related social media websites globally, with more than 20 million monthly users. SA offers a unique setting for our investigation because of its dual content structure. Contributors can share investment ideas via (a) opinion articles, which undergo editorial review and approval before publication, or (b) comments on these articles, which typically appear immediately with minimal oversight.[1] This variation in content moderation allows us to examine how platform governance relates to both the prevalence and outcomes of toxic content. The platform's size and influence make it particularly relevant for understanding how social media toxicity relates to market behavior.

Measuring toxic content in financial discussions is challenging, though. Traditional sentiment analysis tools (e.g., Loughran and McDonald, 2011) are not designed to capture the nuanced and informal ways toxic behavior manifests. Moreover, the flexible nature of social media language means that toxic content can evolve to evade simple keyword-based detection. To address these challenges, we leverage recent advances in machine learning for toxic content detection. Specifically, we employ Google's *Perspective API*, a state-of-the-art system trained on millions of online comments to identify hostile, harassing, or abusive language.[2] *Perspective* was specifically designed for microblog-like contexts and trained on a dataset consisting of

[1] SA occasionally deletes comments that are detrimental to civilized conversation, and they screen comments from new users more heavily before publishing them to minimize slander and trolling. Thus, we likely underestimate the actual level of toxicity in comments, as the most toxic content may be removed before we can observe it.

[2] *Perspective* is an API that enables developers/researchers to identify and filter harassment and abusive language using a toxicity detector running on Google's servers. *Perspective* defines toxicity as "a rude, disrespectful, or unreasonable comment that is likely to make one leave a discussion." Jigsaw partnered with online communities and publishers, such as *Wikipedia* and *The New York Times*, to implement this toxicity measurement system.

online comments. It scores several different attributes (such as insult, obscenity, identity hate, sexual harassment, etc.), and we use its general "toxicity score" (*ToxicLang*) that attempts to capture various manifestations of toxic speech.[3]

We expect that toxicity is related to tone, as they can be different ways of expressing emotion and opinion. However, toxicity is a unique construct from tone, with more extreme and potentially detrimental effects on receivers given its off-putting and disparaging tendencies. To distinguish the role of toxic content from general sentiment, we include controls for tone throughout the analyses, using several traditional and emerging tone measures: those proposed by Loughran and McDonald (2011) (LM, hereafter) and Bozanic, Chen, and Jung (2019) (BCJ, hereafter), Huang et al.'s (2023) FinBERT measure, and sentiment analysis tools TextBlob and VADER.[4] In addition, because comments have informal and evolving language, nuanced and sarcastic content, and often intermingled references to multiple entities (i.e., firm, peer firms, other commenters) that make traditional tone estimation difficult, we repeat analyses with our own measure of comment tone developed by prompting ChatGPT to estimate whether a comment is negative, positive, or neutral toward the firm.

Our empirical strategy proceeds in several stages. First, we examine the drivers and distribution of toxic content across firms, users, and time. Second, we study how past exposure to toxic content is related to future platform participation, allowing us to identify potential feedback effects on user behavior. Third, we analyze the relation between toxic content and retail trading patterns, examining trading volume and the informativeness of retail order flow. Finally, we investigate the broader market efficiency implications by studying how toxicity is

[3] See Appendix B for examples of toxicity within articles and comments in our sample.
[4] We tabulate results controlling for comment tone using the LM and FinBERT measures as these had the highest classification accuracy (F1 scores) from this group of measures. We describe results using the other tone measures.

related to price discovery around significant information events.

Our initial analysis documents that social media toxicity reaches a broad set of firms and users. We find an increase in social media toxicity over time, particularly in comments. By 2020, over 50% of firms experience toxic comments in their coverage, though most firms receive fewer than five toxic comments annually.[5] Importantly, this toxicity is not concentrated among a small group of users—about 30% of platform users make at least one toxic comment annually, but few make more than five or ten toxic comments, suggesting that platform toxicity emerges from broader behavioral patterns rather than a few disruptive participants.[6]

We next examine the drivers of toxic content and find that several firm and content characteristics are significantly related to toxicity. Firms with better performance and greater return volatility receive more toxic articles and comments, and larger firms receive more toxic comments, suggesting greater investor attention and disagreement drive toxicity. We also find that tone is negatively correlated with toxicity; more positive articles and comments are less likely to include toxic language. However, the correlation between toxicity and tone is moderate and does not absorb other determinants. Further, we find (untabulated) that while toxic comments are more likely to have a negative tone, a substantial portion are neutral or positive.[7] Overall, the analyses support our assertion that toxicity is a unique construct from tone.

In addition, firms led by female CEOs also receive significantly more toxic comments. The relation for female-led firms is robust to various specifications, including a difference-in-differences design using male-to-female CEO turnover that helps address endogeneity

[5] For these descriptives, we label "toxic comments" as those with a top-decile toxicity score in our sample.

[6] Consistent with toxicity being a broader pattern, we repeat our main analyses in the paper after excluding the top 1% most toxic articles and comments, and all coefficients of interest remain the same sign and significant.

[7] The proportion of negative comments is 20% to 40% greater for toxic versus non-toxic comments, depending on the tone metric, but 37% to 68% (15% to 20%) of toxic comments have neutral (positive) tone. See Sections 3.2 and 4.2 for more discussion of the relation between toxicity and tone.

concerns, although we caveat that only 5.5% of our sample has a female CEO. This finding aligns with recent evidence of women reporting more severe forms of online harassment (Powell and Henry, 2015; Duggan, 2017). Further, toxicity's presence in the typically unmoderated comments rather than the moderated articles suggests an important role for platform oversight in constraining inflammatory discourse.

We then examine potential outcomes associated with toxicity on financial social media, documenting three main findings. First, toxic content is associated with distinct patterns in platform engagement. Specifically, we find that toxic discourse – whether in articles or comments – is associated with a shift toward more toxic engagement in the future: less future participation by non-toxic contributors and more by toxic contributors. This dynamic suggests a feedback loop where toxicity alters the composition of platform participants over time, potentially fostering an environment that amplifies inflammatory discourse. In financial social media contexts, this shift in participant composition could mean reduced informativeness of crowdsourced investment opinions in the long run.

Our second major analysis uses retail trading behavior to assess likely participant responses in capital markets. We find that toxic comments are associated with higher retail trading volume but also lower informativeness of retail order flow. This pattern suggests that while toxic content may attract attention and subsequent trading activity, it potentially impairs retail investors' ability to process value-relevant information.

Our third set of analyses focuses on broader capital market effects. We first find that comment toxicity (but not article toxicity) is associated with negative returns around article publication. We then turn to the speed of information pricing, and we find that higher levels of toxic content around earnings announcements are associated with significantly slower price discovery, with a more robust effect for comment toxicity. This relation persists after controlling for traditional measures of information environment quality, firm characteristics, and tone. These findings suggest that toxic discourse could introduce additional barriers to efficient information processing, compounding the frictions highlighted in prior research (Blankespoor et al., 2020).

Our study makes two primary contributions. First, we extend research on social media's role in financial markets by documenting the existence of toxicity in less moderated portions of legitimate and informative financial media platforms, as well as toxicity-related frictions in information processing. Prior studies establish the value-relevance of social media opinions (Chen et al., 2014; Jame et al., 2016; Tang, 2018), and we find that the benefits of social media for market efficiency may be partially offset by the costs of toxic discourse. Further, our evidence that toxic content is self-reinforcing (i.e., seems to deter engagement from non-toxic users and attract more toxic contributors) could mean continued or increasing negative effects of toxic social media attention for information processing and price discovery. Thus, our evidence reinforces the importance of considering the potential costs along with the benefits of social media for information dissemination and processing (e.g., Blankespoor, Miller, and White, 2014; Lee, Hutton, and Shu, 2015; Jung et al., 2018; Jia et al., 2020; Cookson, Mullins, and Niessner, 2024).

Second, we contribute to the literature on retail trading behavior by demonstrating how platform toxicity is related to both trading intensity and informativeness. Recent work highlights the increasing presence of retail investors in capital markets and social media's potential democratization of investment research (e.g., Farrell et al., 2022). Our results suggest that platform toxicity may impair retail investors' ability to process information effectively despite increased engagement. This finding has important implications for understanding how social media affects market participation and efficiency.

2. Background and Motivation

2.1 Equity Research on Social Media Platforms

Equity research on social media platforms is increasing, bringing fundamental changes to the market for research previously dominated by investment banks. First, social media platforms offer a low-cost way of gathering information about stocks. Second, the structure of online platforms encourages and enables the sharing of information to reach a wide audience. Finally, social media analysts are arguably less influenced by incentives to issue biased reports to generate trading commissions or support investment banking deals for their brokerage houses as compared to sell-side analysts (e.g., Jame et al., 2022).

A growing literature finds that social media platforms such as Estimize, Seeking Alpha (SA), Stocktwits, and Twitter provide market participants with relevant information. Chen et al. (2014) document that the tone of user-generated articles and comments on SA significantly predicts future stock returns and earnings surprises, and the aggregated sentiment of Twitter posts is similarly correlated with future sales and earnings announcement news (Tang, 2018; Bartov et al., 2018). Jame et al. (2016) find that Estimize forecasts provide incremental value over analyst forecasts and firm characteristics when forecasting earnings and measuring the market's expectation of earnings. In addition, the lower bias of Estimize forecasts disciplines traditional analysts to reduce their forecast bias (Jame et al., 2022). Turning to the benefits to investors, Farrell et al. (2022) find that SA reports facilitate informed trading by retail investors. Gomez et al. (2024) provide evidence that SA reduces information asymmetry, and SA coverage of a firm during a fiscal quarter reduces sophisticated investors' information advantage during earnings announcements.

However, the fundamental characteristics of financial social media also raise concerns for investor information use and efficient capital market functioning. For example, the opportunity for anonymity leads to credibility concerns. Anonymous online forecasts and opinions are of lower quality and have muted stock market reactions (Brown and Khavis, 2018; Dyer and Kim, 2021). Similarly, investors respond less to SA articles when the authors don't have "skin in the game", i.e., personal financial positions in the stocks (Campbell et al., 2019). Another concern is that limited oversight could lead to "fake" articles that drive uninformed trading (e.g., Kogan et al., 2023; Liu and Moss, 2024). More broadly, media and regulators raise questions about social media discussions and coordination, potentially leading to uninformative and extreme price movements (e.g., GameStop and AMC).[8] In general, the informality and interactivity of social media can fundamentally improve financial discourse but also leave it vulnerable to distracting, irrelevant content (e.g., Blankespoor, 2018).

2.2 Online Toxic Discourse and Information Processing

We focus on a new potential concern enabled by limited oversight and anonymity: online toxic discourse. Toxic language, harassment, abuse, and hate speech on online platforms manifest across a spectrum, ranging from relatively mild forms like name-calling and social embarrassment to more severe behaviors, including threats and coordinated attacks.[9] Toxic

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[8] Then-SEC Chairman Gary Gensler said, "*Many of our regulations were largely written before these recent technologies and communication practices became prevalent. I think we need to evaluate our rules, and we may find that we need to freshen up our rule set.*" (https://www.wsj.com/articles/sec-studying-whether-new-rules-are-needed-for-apps-that-gamify-trading-chair man-says-11620239971)

[9] Hate speech is defined as communications of animosity or disparagement of an individual or a group on account of a group characteristic, such as race, color, national origin, sex, disability, religion, or sexual orientation (Nockleby, 2000). Hate speech is a subset of our broader construct of toxic language, which also includes rude and off-putting language, as defined by the collaborative group developing Google's *Perspective*.

language is a growing concern for social media platforms, marketers, and governments, and 41% of Americans report experiencing at least one of these forms of toxic speech (e.g., Powell and Henry, 2015; Vogels, 2021).[10] Vogels (2021) reports that 55% of people believe online harassment is a major problem, and Aleksandric et al. (2024) find that Twitter users responding to toxic conversations are more likely to express anger and sadness.

These statistics are from general online contexts, though, not financial social media. Given online financial posts' information focus and on-average informativeness (as described above), these conversations might not attract toxic discourse. Further, financial social media platforms might be able to avoid toxicity through careful content moderation. General-purpose online platforms invest heavily in content moderation systems (e.g., this need was a driving force behind the collaborative development of the toxicity tool we use, *Perspective*), and financial platforms are likely motivated to moderate as well.

However, the broad and varied objectives and preferences of online contributors and investors could motivate toxic discourse despite the platform's goal of information-focused analysis. And, effective content moderation can be challenging, especially in specialized contexts like financial discussions. Traditional content moderation approaches struggle with technical language and rapidly evolving terminology (Sarker et al., 2020). These difficulties could be particularly acute in financial settings, where legitimate criticism must be distinguished from inflammatory discourse. Further, real-time interaction means toxicity can spread rapidly before moderation systems can intervene, and self-reinforcing cycles of toxicity could occur, with initial toxicity deterring non-toxic participation and attracting more toxic

[10] Also see, e.g., https://www.goodtherapy.org/blog/trolls-toxicity-surviving-online-harassment-0529197, https://time.com/6295711/twitters-hate-content-advertisers/, https://www.chathamhouse.org/2021/07/new-uk-bill-can-fight-fresh-wave-online-racist-abuse

contributors. Given this, toxicity is likely more present and problematic in platforms that have more real-time interaction and less oversight. SA's structure provides useful variation for examining this, including 1) articles that are reviewed and released with some delay and 2) comments (on articles) that are released more quickly with less oversight and thus more potential for toxicity.

If toxicity exists in online financial discourse, a natural concern is whether and how it affects communication, information processing, and market functioning. Given research findings that processing costs influence investors' information choices and market outcomes, barriers to effective communication can have meaningful economic consequences (see Blankespoor et al., 2020). We propose that toxicity could influence investor information processing for several reasons.

First, toxicity could distract investors from processing firm information and instead motivate them to respond with heuristics or emotion, which in turn leads to less efficient price formation. Findings from a variety of contexts suggest intense or emotional situations deter typical information processing and performance. For example, Anderson et al. (2014) find that individuals exposed to incivility while learning about a new topic online appear more likely to resort to heuristics; they have more polarized views afterward that are consistent with each of their diverse prior belief structures and related heuristics. Hall and Madsen (2022) find that intense roadside safety warnings (tabulating traffic accident deaths) lead to distracted drivers, impeding their cognitive processing and impairing their driving performance. Lo, Repin, and Steenbarger (2005) find that day traders who report more intense emotions with trading make less profitable trading decisions. Building on these ideas, we argue that intense toxic language in SA comments might similarly impair investors' information processing capabilities due to distraction, emotion-driven decisions, or reliance on heuristics. This is especially salient for retail investors, who seem more prone to distraction given existing evidence of attention-driven trading in stocks with high media attention or disagreement (e.g., Antweiler and Frank, 2004; Barber and Odean, 2008; Barber et al., 2022).

Second, because toxic content is intermingled with other opinions and information, investors using social media as an information source must determine whether toxicity is simply inflammatory rhetoric or conveys relevant information through its intensity. Given the informality of toxic language and focus on disparagement rather than relevant evidence, this requires processing additional information in the context of the comment as well as assessing information credibility. Even if investors do not find the toxicity convincing, its existence likely draws their attention and demands further assessment. For example, Mutz and Reeves (2005) perform several experiments in which they manipulate the level of incivility in video political exchanges. They find that viewers exposed to incivility were more emotionally aroused yet assessed politicians as less credible.

Third, the presence of toxicity could be unpleasant enough that a subset of investors who would have become informed instead completely avoids toxic content and/or firms with toxic content. This avoidance is consistent with Perspective API's definition of toxic language as statements that make "one leave a discussion," and would reduce the pool of informed traders and slow market price formation.

Overall, there are potentially important tradeoffs in financial social media. While platforms' openness and flexibility contribute to documented benefits for market efficiency, these same features may enable forms of discourse that distract, increase processing costs, and reduce the pool of informed participants, ultimately slowing price formation. The potential for detrimental distraction and increased processing costs is particularly important for retail investors who increasingly rely on social media for investment decisions yet typically have fewer resources (Farrell et al., 2022). Understanding how toxicity affects both platform participation and market outcomes is increasingly important as social media and retail investors play growing roles in financial markets. Our study contributes to this literature by documenting platform toxicity's relation with user behavior, retail trading patterns, and price formation.

3. Methodology and Data

3.1 Measuring Social Media Toxicity

Identifying toxic discourse within social media's dynamic and context-dependent language requires sophisticated measurement tools. Social platforms' approaches have included relying on crowdsourcing (upvotes/downvotes), manual moderation, or not allowing comments to mitigate the effect of inappropriate content. These approaches, however, are not always accurate or scalable and can diminish the value of social media. Traditional linguistic methods to automatically identify and remove hate speech can fail due to slight word changes (whether intentional obfuscation of toxic speech or simply rapid evolution of online language) or phrases that are offensive only in certain contexts. The industry and researchers have looked to machine learning as a possible solution given recent advances that have transformed computer vision, speech recognition, and language processing domains.

Specifically, Google's Counter Abuse Technology team and Jigsaw launched a project called *Perspective,* which uses machine learning to detect online insults, harassment, and abusive speech, providing a toxicity score for each input text.[11] Google and Jigsaw developed

[11] https://www.perspectiveapi.com/

the measurement tool by compiling millions of comments from platforms like Wikipedia and *The New York Times* and creating training examples for the model by asking panels of ten people to rate each comment on a scale from “very toxic” to “very healthy” contribution. The goal is to identify language that could be perceived as rude, disrespectful, or likely to discourage participation in discussions. While its primary focus is civility, it is also used by online platforms to prioritize and moderate comments more effectively. For example, *The New York Times* uses it to filter comments, allowing human moderators to focus on the most potentially problematic ones. Perspective API is considered the “state-of-the-art” tool to identify abusive online content (Sarker et al., 2020; Andres and Slivko, 2023). In cross-sample tests, Perspective API presented an accuracy of 0.893 and an F-score of 0.858 (Sarker et al., 2020).[12] Thus, to capture different dimensions of negativity in social media opinions, we use the toxicity scores (*ToxicLang*) from Perspective API’s novel machine-learning algorithms as our primary measure.

3.2 Measuring Tone

Toxicity is related to tone in that they can both be used to convey different levels of emotion and opinion. For example, a social media post may use negative tonal words to convey a negative opinion and then add a toxic phrase to emphasize the intensity of their negative opinion. However, unlike tone, toxicity is fundamentally off-putting or disparaging of others and thus is more likely to change the nature of the message and others’ response to it. Whereas tone is often intended to be grounded in information, toxicity can be loosely or even unrelated to information content and instead used to garner attention, entertain, or further an individual’s

[12] Recent studies also use RoBERTa models to identify toxicity (e.g., Ederer et al., 2024). Also, as hate speech is ever evolving, the Perspective API algorithm is constantly updated to improve accuracy. We calculated our toxicity scores in January 2021.

broader behavioral or social agenda, independent of the primary message of the post. Thus, while toxicity could act to strengthen a tonal message, it could also undermine it by sending a conflicting signal or distracting or offending the receiver. We want to isolate toxicity from tone, so we control for tone in the SA articles and comments throughout.

To control for general sentiment in SA articles, our baseline *Tone* analysis follows Chen et al. (2014) and related literature in using the LM word lists.[13] Further, we also repeat analyses using BCJ sentiment word lists that were designed specifically for analyst report headlines; given SA articles are the online community's version of analyst reports, their tailored wordlist could be relevant in this setting.

To control for general sentiment in SA comments, we first use LM word lists, following research on social media discourse in financial markets (e.g., Bartov et al., 2018, Dyer and Kim, 2021). However, given recent developments in language processing and the nuanced, evolving nature of social media comments, we also consider several alternative measures currently used in the field: BCJ's sentiment list from analyst report headlines, the FinBERT sentiment measures from Huang et al. (2023), TextBlob's sentiment analyzer, and the VADER (Valence Aware Dictionary and Sentiment Reasoner) lexicon-based model focused on social media. Of these, LM and BCJ bring the advantage of being designed for use in financial contexts, and FinBERT has the financial setting advantage as well as more contextual sentiment assessment than LM's and BCJ's dictionary methods. However, all three have the disadvantage of not being focused on the microblog context. TextBlob and VADER bring the advantage of being designed for social media and more contextual evaluation (and VADER especially for emotion in social

[13] We account for negation by also classifying as negative any positive words that are negated (i.e., have a negation word within the three preceding words, using Chen's expanded negation list to account for contractions, see https://www.kaichen.work/?p=399) and similarly classifying as positive any negative words that are negated.

media), but they are not trained for financial contexts.

To evaluate the different measurement approaches, we manually classify a stratified sample of 300 Seeking Alpha comments for tone about the focal company (positive, negative, or neutral). Using this hand-coded sample as our benchmark, we calculate F1 scores, finding that FinBERT and LM are the best classifiers (0.55 and 0.49, respectively, with no statistical difference), followed by BCJ (0.46), VADER (0.42), and TextBlob (0.41). Thus, we tabulate results using both FinBERT and LM to measure comment tone, and we discuss the robustness of results using the other measures. In addition, we develop our own measure of comment tone using ChatGPT and repeat our main analyses; see Section 6.2 for details.

3.3 Data

We use Seeking Alpha (SA) as our source of financial social media content for several reasons. First, SA is one of the largest financial social media platforms, with prior research documenting its significant role in capital market price formation (Chen et al., 2014; Dyer and Kim, 2021). Second, SA's dual content structure – moderated articles and unmoderated comments – allows us to examine how content oversight affects social media toxicity.

We use SA articles from January 2006 to October 2020, along with related user comments posted within the [0,2] days after article publication (all as provided to us by Seeking Alpha). We capture the publication date, author, tagged stock tickers, and the article and comment text. Following prior studies (e.g., Chen et al., 2014; Dyer and Kim, 2021), we keep only articles written by one author and focused on one company to reduce measurement concerns.

Our primary measure captures the toxicity of social media content (*ToxicLang*). We calculate toxicity scores at the sentence level for articles and at the comment level for user responses. The article-level toxicity score is the sum across all sentence-level scores, while the comment-level score is the sum across all comment scores for that article. Article (comment) tone is measured using all the words in the article (comments) when a dictionary measurement method is used (i.e., LM, BCJ), and overall comment tone is the average of individual comment tones when textual assessment methods are used (i.e., FinBERT, TextBlob, VADER).

We collect financial statement information from Compustat, CEO information (including CEO gender) from Execucomp, market data information from CRSP, institutional ownership data from Thomson Reuters' 13F database, SEC filings from the EDGAR dataset, and press releases from Ravenpack. We hand-collect any missing CEO start or departure dates.[14] Finally, we delete all observations with dual CEO appointments or missing information for control variables. Our final sample consists of 121,005 articles for 1,580 firms spanning from January 2006 to October 2020. Table 1 presents the distribution of our sample over time.

3.4 Descriptive Statistics

Table 2 reports the summary statistics for our sample, with observations at the article level. Similar to Dyer and Kim (2021), our average firm is large and profitable, with an average log market value of 10.03 and an average ROA of 3.8%. The average (median) article is 837 (876) words long with a slightly positive (positive) tone, and it has 17 (5) comments that add another 135 (292) words per comment and have positive (neutral) tone. While the average total toxicity score for articles (2.60) is greater than the sum of toxicity of comments (1.78), there is substantially more variation in comment toxicity (std. dev. of 3.41 versus 2.55 for articles), suggesting that extreme toxic content is more prevalent in comments.[15] Appendix B provides

[14] We delete observations for which we cannot find information about CEO start date.

[15] We use the sum of toxicity across entire articles and comments in our main analyses (and control for article and comment length) because we view multiple toxic statements as more exposure to toxicity. However, consistent with the average comment content being more toxic, the average article toxicity score per sentence is 0.05,

examples that illustrate different levels of toxic content in both articles and comments.

Table 3 presents the correlation coefficients across our main variables. Toxicity is generally negatively correlated with tone and positively correlated with firm profitability, growth opportunities, return volatility, article and comment length, and the firm's CEO being female. In addition, comment toxicity is positively correlated with firm size and negatively correlated with CEO tenure. We explore these relations further in a regression in Section 4.2.

4. Trends and Determinants of Toxicity

4.1 Toxicity Existence and Trends Over Time

Figure 1 documents the evolution of toxic content in SA over our sample period. Panel A shows the average toxicity per article sentence, and Panel B presents the average toxicity per comment. Article toxicity declines slightly over time, while comment toxicity increases dramatically in early years and more gradually in later years. This increase in toxicity occurs despite Seeking Alpha's moderation of article content, suggesting that platform governance may face growing challenges in managing user-generated content.

Figure 2 provides a more granular view of toxic comment distribution across firms and SA users. As shown in Panel A, the number of firms receiving toxic comments has steadily increased over time. By 2020, over 50% of firms experience at least one toxic comment on SA articles covering the firm, where toxic comments are defined as those with top-decile toxicity scores (above 0.2). More than 20% (10%) of firms receive five (ten) or more toxic comments, indicating variation in firms' exposure: most experience some toxicity, some experience more frequent toxicity, and some experience none. Panel B provides information about the

whereas the average comment toxicity is 0.07.

distribution of users posting toxic comments. Approximately 30% of users make at least one toxic comment annually. Importantly, toxic commenting is not concentrated among a small group of problematic users; most users who make toxic comments do so infrequently, as evidenced by the relatively small percent of repeat toxic commenters.

4.2 Determinants of Social Media Toxicity

We first examine the determinants of toxic content in financial social media using three measures: (1) the combined toxicity score for articles and comments, (2) article-only toxicity, and (3) comment-only toxicity. This approach allows us to disentangle the factors influencing toxicity in moderated versus unmoderated content. We estimate the following model:

$$ToxicLang_{it} = \beta X_{it} + \sum \theta_{qt} Controls_{qt} + \sum \delta_t Year\ FE_t + \sum \gamma_{ind} Industry\ FE_i + \varepsilon_t \quad (1)$$

where *ToxicLang* refers to one of three toxicity scores: (1) the combined toxicity of both articles and comments, (2) article-specific toxicity *(ToxicLang_Art)*, and (3) aggregate comment toxicity *(ToxicLang_Com)*. Controls include firm characteristics (i.e., size, profitability, market-to-book ratio), CEO characteristics (i.e., gender, tenure), article characteristics (i.e., length, tone), and firm events (i.e., 10-Ks or 10-Q filings, 8-K filings, press coverage) that happen within the week of the article's publication date. We also include industry and year fixed effects. Appendix A provides detailed definitions of all variables. Standard errors are clustered by the author of the SA article.

Table 4 presents the results for the three toxicity variables. We find that better-performing firms and those with higher return volatility experience more toxic articles and comments, consistent with greater investor attention and disagreement for these firms. Articles and comments with more negative tone are more likely to include toxicity.[16] This is consistent with the assumption that individuals are more likely to be rude or offensive toward topics or firms they perceive negatively. However, toxicity also exists in positive and neutral posts, either because they are using offensive language to explain a topic in an attention-grabbing way or because they are discussing multiple topics in nuanced ways. See Appendix B for several example posts, along with their toxicity and tone.

Comment toxicity has additional significant determinants. It is greater for larger firms and higher market-to-book firms, again indicating that investor attention can often bring more toxicity in the less moderated user-generated discourse. It is greater for firms led by CEOs with shorter tenure, implying longevity and success bring some protection from toxicity. Finally, firms led by female CEOs are associated with significantly more toxic comments, suggesting that unmoderated spaces may be more prone to inflammatory discourse compared to moderated content. The coefficient of 0.6989 in Column 3 implies a 39% increase in average comment toxicity for firms led by female CEOs. This pattern resonates with prior evidence of gender differences in general platforms, such as Powell and Henry's (2015) findings on gender-based differences in online discourse, and Wu's (2018, 2020) findings that discussions on anonymous online economics forums focus disproportionately on non-professional characteristics like appearance and personal details, while discussions about men center on their academic and professional qualifications. Our findings also build on recent evidence of gender bias in investment choices, recommendations, and question patterns by mutual funds, early-stage investors, and analysts (e.g., Niessen-Ruenzi and Ruenzi, 2019; Ewens and Townsend, 2020;

[16] The relations with concurrent information events are more nuanced. In univariate correlations, all three concurrent event indicators are negatively related to toxicity, suggesting that toxicity is less likely to occur when there is recent new information to discuss. In the regression, the signs vary from positive to negative to insignificant, suggesting their joint inclusion might complicate inferences.

Friedman, 2020; Comprix et al., 2022; Jannati et al., 2023). More generally, our evidence contributes to our understanding of how platform governance influences content characteristics.

5. Consequences of Social Media Toxicity

5.1 Future Platform Engagement

We next examine the potential consequences of toxicity in financial social media, focusing first on its relation with subsequent user participation on the platform. Toxic interactions in online communities are believed to have significant effects on users' participation (Powell and Henry, 2015; Cinelli et al., 2021), but this relation remains underexplored in financial social media contexts. To address this gap, we analyze whether exposure to toxic content reduces future SA participation by non-toxic users and attracts more toxic contributors.

We define non-toxic users as those whose average toxicity score falls below the top decile of the toxicity distribution in the previous year. For each article, we calculate two measures of engagement: (1) the proportion of commenters who are non-toxic, and (2) the proportion of comments coming from non-toxic users. We then estimate how these measures relate to the cumulative toxicity in articles and comments over the previous 90 days.

Table 5 presents our findings. The results reveal a strong negative relationship between past toxicity and future participation by non-toxic users. Higher article toxicity in the past 90 days is associated with a significant decline in the number of non-toxic commenters and the proportion of non-toxic comments. The effect is even stronger for past comment toxicity, suggesting that toxic discourse could be an important factor in attracting more toxic discourse, potentially reducing the proportion of non-toxic discussion on social media.

In untabulated analyses, we document similar relations with the absolute levels of engagement by different user types (rather than proportion). We find that past toxic comments are positively associated with the number of unique toxic users and the number of toxic comments and negatively associated with the number of unique non-toxic users and non-toxic comments. The relations remain statistically and economically significant after controlling for firm and article characteristics, firm events, and general sentiment.

These findings suggest that toxic content can create a self-reinforcing cycle where toxicity encourages more toxicity, perhaps helping to explain the persistence of toxic content in financial social media despite platform moderation efforts. Given that social media platforms increasingly serve as venues for financial information dissemination and price discovery (Chen et al., 2014), these systematic changes in platform composition may have important implications for the quality of financial discourse and subsequent market outcomes.

5.2 Retail Trading Behavior

We next examine the relation between toxicity and retail trading behavior. Retail investors are particularly at risk for information implications of toxicity given their active consumption of social media financial content (Farrell et al., 2022) and their tendency toward less-informed attention-driven trading (e.g., Antweiler and Frank, 2004; Barber and Odean, 2008; Barber et al., 2022). While our primary focus is toxicity and information processing, we first ask whether retail investor attention increases with toxicity. We estimate the following model:

$$RetailVolume(RetailPercent)_{it} = \alpha + \beta_1 ToxicLang\_Art_{it} + \beta_2 ToxicLang\_Com_{it}$$

$$+\gamma Controls_{it} + Year\ FE_t + Industry\ FE_i + \epsilon_{it} \qquad (2)$$

RetailVolume (RetailPercent) is the retail trading activity (retail trading as a percentage of total trading) in the [0,2] day window following article publication. We identify retail trades using the Boehmer et al. (2021) method on TAQ data. We conduct this test on articles published between 2010 and 2020, as Boehmer et al.'s (2021) method works best after 2009. We include controls, industry fixed effects, and year fixed effects as before.

Table 6 presents our findings. While article toxicity shows no significant relation with retail trading, comment toxicity is strongly positively associated with both measures of retail activity. These effects are robust to controlling for article and comment length, suggesting that toxicity attracts retail attention beyond any general effect of increased discussion.

We then turn to our main question of how toxicity is related to information processing. Following Farrell et al. (2022), we focus on the informativeness of retail order flow and examine the relation between retail order imbalance and subsequent returns within our sample of SA articles. We estimate the following empirical specification:

$$CAR[3,7] or\ [8,12]_{it} = \alpha + \beta_1 Retail_{OIB_{i,t}} + \beta_2 Retail_{OIB_{i,t}} X\ ToxicLang\_Com_{it}$$

$$+ Retail_{OIB_{i,t}} X\ ToxicLang\_Art_{it} + ToxicLang\_Art_{it} + ToxicLang\_Com_{it}$$

$$+ \gamma Controls_{it} + Year\ FE_t + Industry\ FE_i + \epsilon_{it} \quad (3)$$

CAR is cumulative abnormal return in either the [3,7] or [8,12] window after article publication, calculated by subtracting the market return from the firm's daily return in those windows. *Retail OIB* is the retail order imbalance, calculated as the retail buy trading volume minus retail sell trading volume, divided by the sum of retail buy and sell trading volume, all within the [0,2] days of article publication. We again identify retail trades using the Boehmer et al. (2021) algorithm on TAQ data, and we designate them as buys or sells using the Lee and

Ready (1991) algorithm per Barber et al.'s (2024) recommendations. We include controls, industry fixed effects, and year fixed effects as before.

Table 7 shows that retail order imbalances more negatively predict future returns as comment toxicity increases. The interaction between retail order imbalance and comment toxicity is negative and significant for both near-term returns (CAR[3,7]) and longer windows (CAR[8,12]). This pattern suggests that while toxic content drives retail trading volume, it seems to impair their ability to process value-relevant information or motivate them to trade on attention or heuristics rather than information.

Overall, the findings imply that while social media platforms can democratize investment research and inform retail investors (Farrell et al. 2022), toxicity on the platforms detracts from this informativeness and instead contributes to attention-driven trading.

5.3 Market-wide Response and Price Discovery

We turn next to market-wide outcomes of price response and speed of price discovery to better understand the broader potential implications of toxicity.

5.3.1 Short-window Stock Price Reaction

While our primary focus is information processing implications of toxicity, we first explore the immediate price reactions around article publications to examine the extent of investor attention to toxicity. We estimate the following:

$$CAR[-1,1]_{it} = \beta_1 ToxicLang\_Art_{it} + \beta_2 ToxicLang\_Com_{it} + \gamma Controls_{it} + YearFE_t$$

$$+IndustryFE_i + \epsilon_{it} \quad (4)$$

where *CAR[-1,1]* is the cumulative abnormal return in the [-1,+1] window around article publication, calculated by subtracting the market return from the firm's daily return in that window. We include controls, industry fixed effects, and year fixed effects as before.

As shown in Table 8, article toxicity has no significant association with stock returns, but comment toxicity has a significant negative relation with stock returns.[17] This negative relation suggests informed investors either 1) believe that investors are using toxicity to reveal their legitimate concerns about the company or 2) are more likely to exit their trading interest in the company given the toxic information environment, exerting downward price pressure.

5.3.2 Speed of Price Discovery

We turn to the speed of price discovery to examine the price formation implications of toxicity more fully. If toxicity distracts investors, increases their processing costs, or reduces the pool of informed participants, price formation would slow. To examine toxicity's relation to price formation, we analyze price discovery around earnings announcements using the following model:

$$IPE_{it} = \beta_1 ToxicLang\_Art_{it} + \beta_2 ToxicLang\_Com_{it}$$

$$+ \sum \theta_{qt} Controls_{qt} + \sum \delta_t \, YearFE_t + \sum \gamma_{ind} \, IndustryFE_i \varepsilon_t \quad (5)$$

We focus on earnings announcements given their role as one of the primary firm information events and the focus of many SA articles. Following prior studies (e.g., Butler et al., 2007; Blankespoor et al., 2018; Blankespoor et al., 2020), *IPE* is an Intraperiod Price Efficiency (IPE) metric around the earnings announcement to capture the speed at which the earnings announcement information is incorporated into stock prices. We measure IPE using

[17] Results are consistent using a [0,2] window instead. Also, we find a significantly positive relation between comment toxicity and absolute stock returns (untabulated), controlling for absolute tone and the other variables, consistent with initial investor interest varying with toxicity.

several windows around the earnings announcement ([-1,+2] and [-3,+3]) with the goal of incorporating SA articles posted in the days leading up to the earnings announcement.[18] To calculate the IPE metric, we first estimate the proportion of the cumulative abnormal return recognized at the end of each day during the [-1,+2] (or [-3,+3]) window. We then estimate the area under the curve, with larger areas corresponding to faster price discovery. Following prior literature, we use the IPE (adjusted IPT metric) to adjust for any overreaction and reversal during the return measurement window (Blankespoor et al., 2018; Blankespoor et al., 2020). Equation (6) shows the calculation for IPE for the [-1,+2] window:

$$IPE_{[-1,+2]} = \sum_{t=-1}^{t=+2}[1 - (\frac{|AbnReturns_2 - AbnReturns_t|}{|AbnReturns_2|})] \qquad (6)$$

In line with the existing literature, we also exclude observations with absolute cumulative abnormal returns of less than 2% in the event window to reduce measurement noise due to a small denominator.[19] To capture the toxicity of articles and comments within the [-1,+2] ([-3,+3]) event window, we aggregate individual *ToxicLang_Art* (for articles) and *ToxicLang_Com* (for comments) for all articles on SA within that period. Similarly, we aggregate our tone measures to assess the overall sentiment of articles and comments surrounding the event window. Finally, we also include controls, industry fixed effects, and year fixed effects.

As shown in Table 9, toxic comments are associated with significantly slower price discovery. Comment toxicity exhibits negative coefficients across all measurement windows, with statistical significance at the 1% level. The relation remains robust when examining longer

[18] While the windows are narrow, we see sufficient SA articles in these windows to draw inferences. Specifically, of the articles in our final sample posted within 14 days before or after the earnings announcement, 44% are posted within 3 days before or after the earnings announcement.
[19] In untabulated analyses, we find similar results if we only exclude absolute $CumAR_2(CumAR_3)$ less than 1%.

windows ([-3,+3]), indicating that the negative effects on price discovery extend beyond the immediate post-announcement period.

Combined with our earlier findings, toxic content in social media comments seems to not only draw retail investors' attention and reduce their trading informativeness, but also introduce noise into the market's information processing that slows price formation. These results are consistent with theoretical predictions and empirical findings of information processing costs reducing market efficiency. Further, they highlight that toxicity on social media platforms is a cost of the platforms' informality and lack of moderation that could affect not only retail investors but also broader market functioning.

6. Additional Analyses

6.1 CEO Gender and Toxicity during CEO Transition Periods

In our determinants analysis, CEO gender is significantly associated with the level of toxic content on social media platforms. To further examine the relation between CEO gender and platform toxicity, we perform two tests. First, we repeat our determinants estimation (model 1, Table 4) using firm fixed effects instead of industry fixed effects. We continue to find (untabulated) a significant positive relation between comment toxicity and female-led firms (coefficient = 0.8024, t-statistics = 6.33). This provides further evidence of gender-driven toxicity holding the firm constant and using changes in the CEO.

Second, we further examine CEO turnover events as a setting where we can compare gender differences while holding firm characteristics effectively constant. Following other studies (e.g., Huang and Kisgen, 2013; Cook et al., 2025), we compare firms that replace a male CEO with a female CEO (*Male_to_Female*) to those that replace a male CEO with another male CEO (*Male_to_Male*) in a short window around CEO turnover date (3 months before and 3 months after).[20] This setting offers several advantages. First, by focusing on transitions, we can observe changes in toxicity while holding firm characteristics constant through firm fixed effects. Second, the short window [-3,+3 months] around transitions helps isolate the role of CEO gender from other time-varying factors. Third, by comparing male-to-female transitions with male-to-male transitions, we can better attribute changes in toxicity to CEO gender rather than general turnover effects.

We implement a difference-in-differences design with the following specification:

$$ToxicLang_{it} = \beta_1 I(Male\_to\_Female) * I(Post) + \beta_2 I(Male\_to\_Female) + \beta_3 I(Post) + \gamma Controls_{it} + FirmFE + YearFE + \epsilon_{it} \qquad (7)$$

I(Male_to_Female) equals one if the firm is transitioning from a male to a female CEO, and zero if the firm transitions from a male CEO to a male CEO. *I(Post)* equals one if the article is published in the three months after the turnover date, and zero otherwise. Our focus is on the interaction of these two variables, and the main effect of *I(Male_to_Female*) is subsumed by the firm fixed effects because none of our sample firms have both forms of CEO transition in our period. We employ entropy balancing to account for observable differences in firm characteristics between male-to-female and male-to-male transitions. This approach reweights the control group (male-to-male transitions) to match the treatment group across two moments of firm characteristics: size, profitability, growth opportunities, return volatility, event indicators (earnings, 8K, and PRs), and earnings surprise. Other variables are as defined earlier, and we include control variables, firm fixed effects, and year fixed effects.

[20] We use a sample period of 2010-2020 (i.e., retail trade informativeness test constraints) to have one sample across all tests.

As shown in Table 10, male-to-female transitions are associated with significantly greater post-transition toxicity than male-to-male transitions when articles and comments are examined together (Columns 1 and 4). When articles and comments are separated, the coefficient remains positive but becomes statistically insignificant (marginally significant) for articles (comments). While the results are weaker than in the main determinants analysis, this is a narrower setting that, by definition, does not capture the vast majority of online discourse. Together, we interpret these as weak but suggestive results that toxic comments are more likely to exist for female CEOs. Given our earlier evidence of toxicity's relation with slower price discovery and reduced retail trade informativeness, disproportionate toxic comments for female CEOs could have disadvantaging information consequences for capital markets.

6.2 Alternative GPT-based Comment Tone Measure

Given the inherent relation of toxicity and tone and the difficulty of assessing tone in informal social media comments, we repeat our main analyses using various measures of comment tone from prior literature, as discussed in Section 3.2. These measures have different strengths and weaknesses, so the stability of our results across them further supports our conclusions. However, they have two weaknesses in common. First, they assess the general sentiment of the comment, rather than sentiment toward the firm (i.e., entity-based sentiment). Online comments' flexible, informal nature often results in less focused discourse; discussion of other entities, groups, or individuals along with the focal firm can introduce noise into traditional sentiment measures. Second, the best sentiment classifier had a 0.55 F1 score in our sample, leaving room for improvement. In this section, we develop and implement an alternative measure of sentiment designed to capture SA comments' negativity toward the firm.

We leverage recent advances in large language models (LLMs) and prompt OpenAI's ChatGPT-4o mini model to estimate each SA comment's sentiment toward the focal firm. We use a zero-shot approach with no finetuning: provide the model with the comment and focal firm name, and ask it to analyze the sentiment of the comment toward the company (including its products, board of directors, and management).[21] To assess the model's performance, we compare its answers to the manually classified firm-specific sentiment in the same stratified random sample of 300 comments used for our other tone validations. We find that the GPT-based measure has an F1 score of 0.7, which is significantly better than the traditional sentiment measures discussed in section 3.2. We believe our measure brings the advantage of more precisely assessing firm-specific sentiment and more flexibly adjusting for nuance and sarcasm in informal comments. However, its ability to identify informal negativity could mean that it assesses toxic language directed at the firm as negative sentiment, slightly blurring the toxicity and tone constructs. Further, because we created the measure, it has not been as widely vetted as the others.

Table 11 presents our key findings after replacing the comment tone measure with our ChatGPT-based comment tone measure.[22] Results are consistent with our main analyses. As shown in Columns 1 and 2, comment toxicity is positively related to trading activity by retail

[21] We calculated our scores during July through November 2024 using the 4o-mini model in OpenAI's API with temperature equal to 0. Our prompt was *"Analyze the sentiment of the following comment in the context of the company or product or board of directors or management in general, its CEO, and the article author or commenter. This comment could be written in response to a firm-related article or responding to another comment. Think step by step and provide a brief explanation (not more than two lines) before deciding the sentiment. Classify the sentiment separately for the company/product/board of directors/management, the CEO, the author/previous commenters, and other aspects unrelated to the company, product, management, board of directors, CEO, or author/commenter. Ensure that the sentiment towards the company is classified as Positive or Negative only if there is a clear and confident indication. Otherwise, default to Neutral. Provide the classification as Positive, Neutral, or Negative, using the JSON format described below."*

[22] We continue to use the dictionary-based method for articles because 1) there is less concern about nuance and varying focus of sentiment within longer-form focused articles, and 2) the GPT-based measure is more cost-prohibitive and difficult to validate in that setting given the article length.

investors. Column 3 displays a negative relation between toxicity and retail trade informativeness; when SA comments are more toxic, retail trading around the article is negatively correlated with returns in the next week, suggesting an uninformative retail response. Column 4 displays a significantly negative market response when comments are more toxic. Finally, comment toxicity continues to be negatively correlated with price discovery around earnings announcements in Column 5, suggesting toxicity can delay information processing around earnings announcements. Overall, our main findings are robust to this alternative measurement of sentiment, reinforcing the role of toxic discourse in capital markets as distinct from tone.

7. Conclusion

This paper examines how toxic content on financial social media platforms relates to user participation and market behavior. Using state-of-the-art machine learning algorithms to measure content toxicity on Seeking Alpha, we document that over half of firms experience toxic comments in their coverage, with toxicity concentrated in unmoderated user comments rather than moderated articles. Comment toxicity is greater for firms with more investor attention (larger firms, better-performing firms) and with more investor disagreement (higher return volatility). Toxicity is negatively related to the tone of SA articles and comments, and firms led by female CEOs receive more toxic comments.

We find that toxicity is associated with increased subsequent participation from toxic contributors, suggesting potential feedback effects. While toxic comments correlate with increased retail trading volume, retail order flow is significantly less informative when comments have high toxicity. Additionally, we find slower price discovery around earnings announcements during periods of elevated toxic comments, indicating broader implications for market efficiency. These results are robust to controlling for a variety of comment tone measures, consistent with toxicity being a distinct construct from tone.

These findings contribute to our understanding of how social media shapes financial markets. While platforms like Seeking Alpha have become important venues for information dissemination and price discovery (Chen et al., 2014; Farrell et al., 2022), our results suggest that toxic comments create friction in this process and highlight that platform governance policies may have meaningful implications for market quality. Fruitful ideas for future research include examining how alternative moderation approaches or platform designs could help maintain the benefits of broad participation while mitigating the costs brought by toxic content.

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Appendix A: Variable Definitions

ToxicLang	Sum of article and comment toxicity. We use *Perspective API* to score both articles and individual comments posted within the [0,2] day window of article publication with regards to Toxic language from 0 to 1, with higher scores indicating greater toxicity. We calculate toxicity scores at the sentence level for articles and aggregate it to the article level. For comments, we calculate toxicity scores at the comment level.
ToxicLang_Art	Sum over the article of each sentence's toxicity score from Perspective API.
ToxicLang_Com	Sum of the toxicity score from *Perspective API* for all comments within the [0,2] day window of article publication.
Agg_ToxicLang_Art (Agg_ToxicLang_Com)	Aggregate *ToxicLang_Art* (Aggregate *ToxicLang_Com)* for all articles (comments) within the earnings announcement windows. For the [-1,+2] ([-3,+3]) window, sum *ToxicLang_Art* (*ToxicLang_Com)* for all articles (comments) published during the [-1,+2] or [-3,+3] period depending on the specification, where day 0 represents the earnings announcement date.
Tone_LM_Art, (Tone_LM_Com)	Proportion of net positive words, i.e., positive words minus negative words, used in the articles (comments) relative to the total number of words used in the articles (comments) using the Loughran and McDonald (2011) dictionary.
Agg_Tone_LM_Art, (Agg_Tone_LM_Com)	Proportion of net positive words, i.e., positive words minus negative words used in the articles (comments) relative to the total number of words used in the articles (comments) using the Loughran and McDonald (2011) dictionary within [-1,+2] or [-3,+3] days around the earnings announcements, depending on the specification.
Tone_BCJ_Art, (Tone_BCJ_Com)	Proportion of net positive words (positive words minus negative words) used in the articles (comments) relative to the total number of words used in the articles (comments) using the Bozanic, Chen, & Jung (2019) dictionary.
Tone_FinBERT_Com	Average tone of comments within the [0,2] day window of article publication, using FinBERT (Huang et al., 2023).
Agg_Tone_FinBERT_Com	Average *Tone_FinBERT_Com* of the comments for articles published within [-1,+2] or [-3,+3] days around the earnings announcements, depending on the specification.
Tone_GPT_Com	Average tone of comments within the [0,2] day window of article publication, using prompted GPT4o-mini model. See Section 6.2 for details.
RetailVolume	Log(1+ Retail Trading Volume), where Retail Trading Volume is total number of shares bought and sold by retail investors during [0,2] days around article publication, using the Boehmer et al. (2021) algorithm on TAQ data to identify retail trades.
RetailPercent	The percentage of trading activity (volume of shares bought and sold) by retail investors, using the Boehmer et al. (2021) algorithm on TAQ data to identify retail trades.
Retail OIB [0,2]	(Retail Buy Trading Volume – Retail Sell Trading Volume)/(Retail Buy Trading Volume + Retail Sell Trading Volume), where Buy and Sell Trading Volumes are calculated within the [0,2] days of article publication date. Retail trades are identified using the Boehmer et al. (2021) algorithm on TAQ data and buy versus sell

	designation is identified using the Lee and Ready (1991) algorithm, following Barber et al. (2024).
IPE	Intraperiod price efficiency metric (Adjusted intraperiod price timeliness metric) based on Butler et al. 2007; Blankespoor et al. 2018; Blankespoor et al. 2020 and calculated for various windows around the earnings announcements.
CAR	Equally-weighted market-adjusted cumulative stock return during the [-1,+1] window around the article posting, or the [3,7] or [8,12] window after the article posting, as marked in the variable name. Returns data are from CRSP daily and CRSP index.
LogMVE	The natural log of the market capitalization as of the end of the fiscal quarter prior to the article posting date.
MTB	Market-to-book ratio, calculated as the book value of common equity divided by market capitalization as of the fiscal quarter prior to the date of article posting
ROA	Return on assets, calculated as net income divided by total assets as of the fiscal quarter prior to the date of article posting
RetVol	The prior stock return volatility, calculated as the standard deviation of daily market-adjusted stock returns over the event days [-91, -2] relative to the date of article posting
Ind_filing	Indicator variable which takes the value of one if the firm filed its quarterly earnings over event days [-6, 0] relative to the date of article posting, and zero otherwise
Ind_8ks	Indicator variable which takes the value of one if the firm files Form 8-K over event days [-6, 0] relative to the date of article posting, and zero otherwise
Number_prs	The number of firm-initiated press releases in Ravenpack with a relevance score of 95 or higher over event days [-6, 0] relative to the date of article posting
Length_Art (Length_Com) [Length]	The sum of the natural log of one plus the number of words used in the articles (comments within [0,2] days of the article) [articles and comments].
Agg_Length_Art (Agg_Length_Com)	The sum of the natural log of one plus the number of words used in all the articles (comments within [0,2] days of the article) published on SA within the [-1,+2] or [-3,+3] days of earnings announcement, depending on the specification.
Sentences_90days (Comments_90days)	Total number of sentences in articles (number of comments within [0,2] days of the article) about the firm published during the 90-day period ending 5 days before the current article date.
I(Female)	Indicator variable that equals one if the CEO of the firm is female, zero otherwise, based on Compustat Execucomp.
Log_Tenure	Logarithmic of one plus the number of years that the CEO is at the job.
Rank_EarnSurp	Decile rank of earnings surprise, where earnings surprise is calculated as the seasonally adjusted earnings change for the firm, comparing current quarter earnings of the most recent quarter with the same quarter from the previous year.

I(No Article)	Indicator variable that equals one if a firm had no Seeking Alpha article during the respective IPE window

Appendix B: Example Articles and Comments from SA

This Appendix provides excerpts from SA articles and comments in our sample. Panel A presents an example article. We highlight several sentences where the author is using toxic language and provide sentence-level toxicity scores and tone. Panel B presents some comments from our sample with their toxicity scores and tone. The links to the posts are available upon request.

Panel A: Article ID: 221602 (Article Toxicity – 22.39 (99th percentile))

[…]

Yahoo's home page no longer seems to constantly feature stories involving the Kardashians and Paris Hilton. (From the bottom of my heart, thank you. And thank you for finally fixing many of the glitches in Yahoo's calendar.) Also, just when I thought Yahoo's fantasy sports couldn't get any better, you outdid yourself yet again (the new linear stat graphs are wonderful). Yet, as you know, Yahoo still has problems. I want to make sure these problems are on your radar screen, so it's time to take the red pill. Problem 1: Yahoo Tailors its Content to Maximize Eyeballs, another Way of Saying it Emphasizes the Lowest Common Denominator, i.e., Superficial Content over Substance At this year's annual meeting, I told you Yahoo's front page had gotten so asinine, I had switched to your main competitor's home page [Toxicity: 0.718; Tone: Negative]. I'm still not back, because for the most part, your front-page features stories I've seen before or items I don't care about. In the future, content will be king, and right now, you mostly recycle other people's content based on popularity. Well, it turns out the popular kids on the internet love asinine, superficial stories, and when you move with that crowd, you lose credibility with the nerds, geeks, jocks, goths, rebels, and recluses--i.e., everyone but the cheerleaders and their admiring followers [Toxicity: 0.512; Tone: Neutral]. Is that really the direction you want to go? Headfirst into the land of the average and the Simpsons' Ralph Wiggum? And do you really think advertisers want to display ads on a website that has no focus? Wouldn't it make more sense to break up Yahoo into multiple sites, where you could tailor content (and ads) to more specific groups of people?

[…]

Panel A: Article ID: 4140457 (Article toxicity – 3.005 (75th percentile))

[…]

Despite being very skeptical, the poster said that a showroom employee noted the following information (bold is mine): The lady at the front of the line overheard my conversation and tried to assure me it wouldn't be that long and that they were ramping up production. I spouted off how they weren't even supposed to get up to 5,000 per week until the year is half over. She gave me a knowing look and said that they're getting the numbers from corporate and that they're up. <u>I raised my eyebrows and gave her a crap look [toxicity: 0.8355; tone: 0]</u>. She gave me the same look again. <u>I gave her a disgusted crap look with an arm fold</u> [Toxicity: 0.768; Tone: Neutral]. Then, she glanced sideways looked back at me and said more quietly "4,000 per week right now." Considering that Tesla wasn't even at 1,000 units per week at the end of December, it seems highly skeptical that they have gotten to 4,000 in just a couple of weeks. Obviously, management wants to put on a good face to keep people from canceling their deposits, but I hope either management or employees aren't handing out completely false information [Toxicity: 0.163; Tone: Negative].

[…]

Panel B: Comments Sample

Example 1: High Toxicity and Negative Tone
Comment ID: 6901951
Firm Name: 8X8 INC

Comment Text: *"The management team is horrible because the CEO has failed on every single level to attract a real investment bank to cover the company. As I have previously written in an article about 8x8, this company is being covered by some of the worst broker-dealers out there: B. Riley (a complete joke with a jackass for an analyst), Craig-Hallum (who are they, do they have any clients at all?), Sidoti (another joke), Northland Securities (they have, three clients, maybe?). It is crystal clear that either this CEO is someone no real firm wants to even speak with because of who he is, or, he is just not competent enough to speak to a large bank. The company has $100 million annual rate in revs, and growing quickly. Instead of real coverage, shareholders have to put up with incremental upgrades and downgrades from an inept imbecile named Mike Crawford at B. Riley.*

Toxicity score: 0.771843 (Toxic – 99th Percentile)
Negative Tone (LM, GPT), Neutral (FinBERT)

Example 2: High Toxicity and Negative Tone
Comment ID: 75924467
Firm Name: NVIDIA CORP

Comment Text: *"So sorry, you suck. You chose wrong. Too bad, you lost. Are you still here? Why? You lost even if you think you won. Get lost loser. Good. Bye. Get. Lost."*

Toxicity score: 0.922793 (Toxic – 99th Percentile)
Negative Tone (LM, FinBERT, GPT)

Example 3: High Toxicity and Negative Tone
Comment ID: 636473
Firm Name: SIRIUS SATELLITE RADIO INC

Comment Text: "*Stock Price be darned, tell the story. Expose Mel Karmazin and Goldman Sachs as crooks...Mel will not delay the rev-split. He will move on it with the first delisting warning letter... Wait and see...SHUT UP SIRI PAID BLOGGERS!!! SHUT UP!!! YOUR WRONG!!! YOU LIE....heheheh LOL."*

Toxicity score: 0.860626 (Toxic – 99th Percentile)
Negative Tone (LM, GPT), Neutral (FinBERT)

Example 4: High Toxicity and Positive Tone
Comment ID: 9959241
Firm Name: SIRIUS SATELLITE RADIO INC

Comment Text: *"What a load of horse c**p. I personally enjoy a professional programming my radio for me. I also enjoy having great talk radio and sports at my fingers. Content is king."*

Toxicity score: 0.806061 (Toxic – 99th Percentile)
Positive Tone (LM, GPT), Neutral (FinBERT)

Example 5: Low Toxicity and Negative Tone
Comment ID: 62707486
Firm Name: KINDER MORGAN INC

Comment Text: *"Thank you for a sobering article. It probably applies to a lot of companies in the energy space. Debt was irresistible at the artificially low rates. At the higher oil prices, it was almost a license to print money.I do not have a position in KMI, but considered it when other members of my stock club jumped in. I was discouraged by my fair value calculation that indicated KMI was very overvalued. Most of the stock price is supported by the large dividend. However, the debt per share is staggering."*

Toxicity score: 0.013333 (Non-toxic – 1st Percentile)
Negative Tone (LM, FinBERT, GPT)

Example 6: Low Toxicity and Positive Tone
Comment ID: 76197965
Firm Name: WELLS FARGO & CO

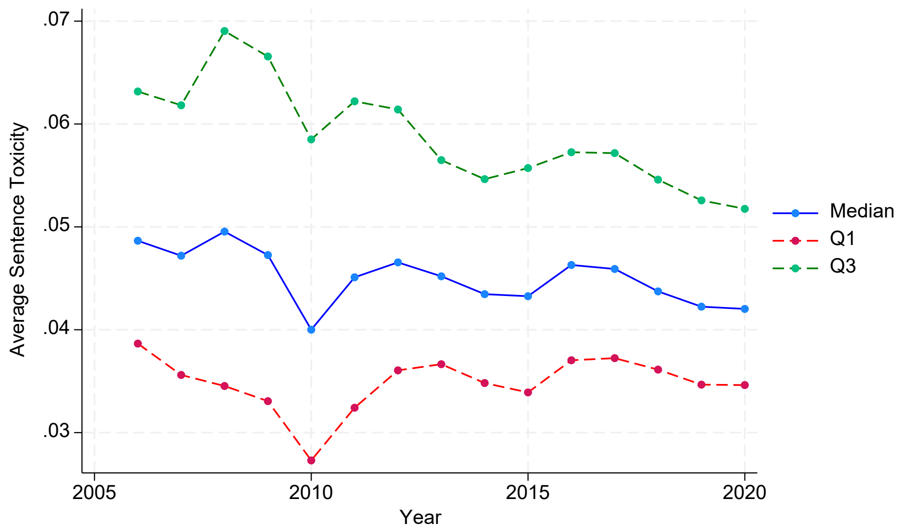
Comment Text: *"Excellent buying opportunity. Was a better opportunity last week, but still very good today."*

Toxicity score: 0.013986 (Non-toxic – 1st Percentile)
Positive Tone (LM, FinBERT, GPT)

Figure 1: SA Toxicity Trends

This figure shows the evolution of toxic content in SA over our sample period. Panel A shows article toxicity (scaled by number of sentences), and Panel B presents comment toxicity (scaled by number of comments).

Panel A: Average Toxicity of Article Sentences by Year



Panel B: Average Comment Toxicity by Year

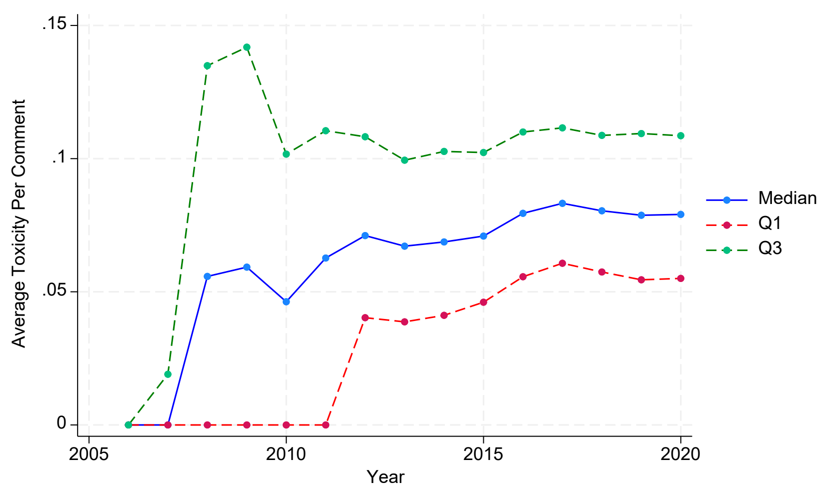
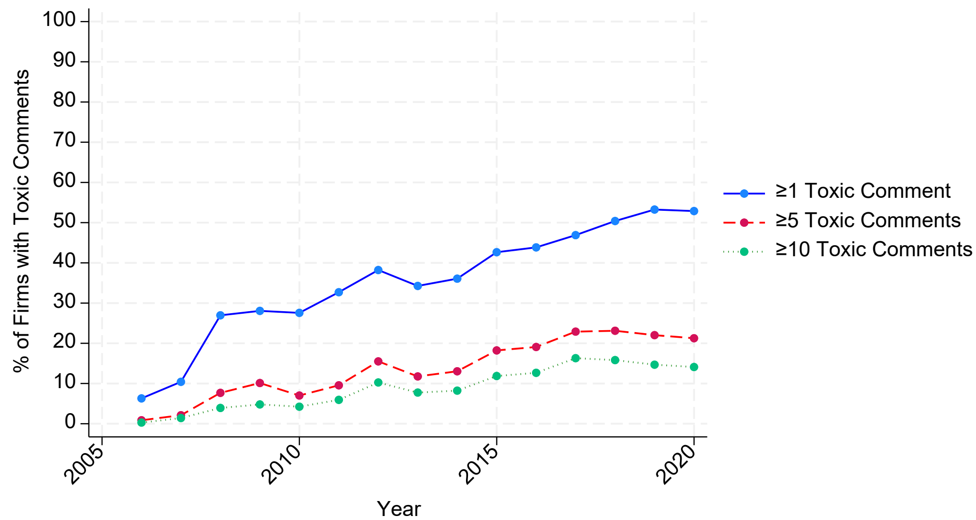


Figure 2: Scope of Toxic SA Comments across Firms and Users

This figure displays the scope of toxic SA comments across firms and users. Panel A shows the annual percentage of firms covered by SA in that year who receive toxic comments, grouped by whether they received 1, 5, or 10 or more toxic comments. Panel B shows the annual percentage of active users (i.e., posting at least one comment) that posted toxic SA comments, similarly grouped. A comment is classified as toxic if its toxicity score exceeds the 90th percentile of the overall toxicity distribution in our sample, focusing on the most extreme cases of toxic content.

Panel A: Percentage of Firms with Toxic SA Comments



Panel B: Percentage of Users Posting Toxic SA Comments

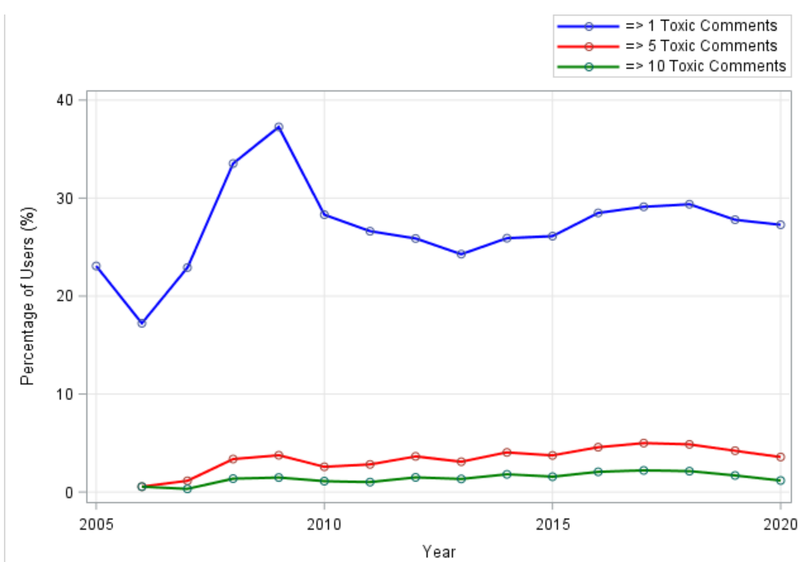


Table 1: Sample Selection

This table reports the number of distinct firms covered by SA during our sample period in Panel A. Panel B shows the number of articles across all the firms, including the number of authors and commenters during each year.

Panel A: Year-wise distribution of firms

Year	#Unique Firms	Freq.	Percent	Cum. %
2006	349	1,446	1.19	1.19
2007	566	4,053	3.35	4.54
2008	586	3,875	3.2	7.74
2009	563	4,455	3.68	11.42
2010	613	4,183	3.46	14.88
2011	691	6,408	5.29	20.17
2012	819	11,299	9.33	29.51
2013	1071	10,235	8.45	37.96
2014	1081	13,082	10.81	48.77
2015	1163	14,083	11.63	60.4
2016	1074	12,179	10.06	70.46
2017	1000	12,362	10.21	80.67
2018	986	8,915	7.36	88.04
2019	967	7,819	6.46	94.5
2020	936	6,661	5.5	100
Total		121,055	100	

Panel B: Year-wise distribution of articles (authors) and comments (users)

Year	#Unique Articles	#Unique Authors	#Unique Users	# Comments
2006	1,446	193	169	547
2007	4,053	394	1,170	3,090
2008	3,875	582	5,789	21,158
2009	4,455	567	5,697	22,566
2010	4,183	550	5,325	20,261
2011	6,408	792	10,425	55,407
2012	11,299	1,162	19,028	141,325
2013	10,235	1,362	19,859	143,384
2014	13,082	1,447	23,659	202,442
2015	14,083	1,495	28,401	240,230
2016	12,179	1,464	29,109	272,665
2017	12,362	1,408	31,598	330,197
2018	8,915	1,067	27,580	260,350
2019	7,819	918	21,777	185,258
2020	6,661	764	22,760	159,615
Total	121,055			

Table 2: Descriptive Statistics - Firm

This table reports descriptive statistics for key variables. The sample consists of 121,055 article observations over our sample period. All continuous variables are winsorized at the 1% and 99% levels.

	N	Mean	Std	Q1	Q2	Q3
ToxicLang	121,055	4.4349	4.7232	1.4865	2.7533	5.4760
ToxicLang_Art	121,055	2.6025	2.5533	1.0757	1.8087	3.0159
ToxicLang_Com	121,055	1.7828	3.4055	0.0628	0.4493	1.7601
Tone_LM_Art	121,055	0.0007	0.0125	-0.0061	0.0014	0.0085
Tone_LM_Com	121,055	0.0013	0.0216	-0.0044	0.0000	0.0047
Tone_FinBERT_Com	121,055	0.1115	0.3228	0.0000	0.0000	0.2353
Tone_GPT_Com	121,055	0.0007	0.4041	-0.1667	0.0000	0.1667
LogMVE	121,055	10.0356	1.9702	8.5818	10.2362	11.6390
ROA	121,055	0.0383	0.0300	0.0196	0.0356	0.0528
MTB	121,055	4.9124	7.8467	1.6309	3.1251	5.8739
StdRet	121,055	0.0192	0.0117	0.0114	0.0156	0.0232
Ind_filing	121,055	0.3219	0.4672	0.0000	0.0000	1.0000
Ind_8ks	121,055	0.0225	0.1482	0.0000	0.0000	0.0000
Number_prs	121,055	16.222	86.195	0.0000	1.0000	9.0000
Length_Art	121,055	6.7278	0.6474	6.3852	6.7765	7.1213
Length_Com	121,055	4.9082	2.8286	3.5553	5.6768	6.9838
Log_Tenure	121,055	7.2995	1.2274	6.6580	7.5110	8.1809
Rank_EarnSurp	121,055	5.4981	2.8724	3.0000	5.0000	8.0000
I(Female)	121,055	0.0551	0.2282	0.0000	0.0000	0.0000

Table 3: Correlation Matrix

Table 3 presents the Pearson correlation coefficients for select article-level variables. All variables are described in Appendix A.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)
(1)	*ToxicLang*	1.0000																		
(2)	*ToxicLang_Art*	0.6842***	1.0000																	
(3)	*ToxicLang_Com*	0.8174***	0.1582***	1.0000																
(4)	*Tone_LM_Art*	-0.1068***	-0.0320***	-0.1216***	1.0000															
(5)	*Tone_LM_Com*	-0.0533***	0.0122***	-0.0833***	0.1370***	1.0000														
(6)	*Tone_FinBERT_Com*	-0.0286***	0.0284***	-0.0616***	0.1436***	0.4127***	1.0000													
(7)	*Tone_GPT_Com*	-0.0410***	0.0129***	-0.0671***	0.1554***	0.2807***	0.4239***	1.0000												
(8)	*LogMVE*	0.2025***	0.0017	0.2825***	-0.0065*	-0.0180***	0.0417***	0.0527***	1.0000											
(9)	*ROA*	0.0691***	0.0159***	0.0845***	0.1130***	0.0365***	0.0343***	0.1270***	0.2094***	1.0000										
(10)	*MTB*	0.0934***	0.0181***	0.1146***	0.0484***	0.0123***	0.0115***	0.0258***	0.1245***	0.1766***	1.0000									
(11)	*StdRet*	0.0481***	0.0184***	0.0500***	-0.1674***	-0.0655***	-0.0848***	-0.1335***	-0.4738***	-0.2259***	-0.0028	1.0000								
(12)	*Ind_filing*	-0.0880***	-0.0824***	-0.0597***	-0.0140***	0.0012	-0.0157***	0.0002	-0.0038	0.0089**	-0.0053	-0.0183***	1.0000							
(13)	*Ind_8ks*	-0.0620***	-0.0310***	-0.0620***	-0.0144***	0.0017	-0.0166***	-0.0145***	-0.1425***	-0.0177***	-0.0237***	0.0621***	0.0852***	1.0000						
(14)	*Number_prs*	-0.0165***	-0.0220***	-0.0051	-0.0616***	-0.0280***	-0.0168***	-0.0460***	0.1607***	-0.0617***	-0.0314***	-0.0586***	0.0409***	-0.0129***	1.0000					
(15)	*Length_Art*	0.4438***	0.5686***	0.1727***	0.0570***	0.0439***	0.0854***	0.0585***	-0.0044	0.0082**	0.0155***	-0.0377***	-0.1286***	-0.0717***	-0.0489***	1.0000				
(16)	*Length_Com*	0.5178***	0.2023***	0.5608***	-0.0863***	-0.0726***	0.0843***	-0.0334***	0.3414***	0.0461***	0.1035***	0.0358***	-0.1203***	-0.1105***	0.0040	0.3307***	1.0000			
(17)	*Log_Tenure*	-0.0166***	0.0016	-0.0247***	0.0524***	0.0167***	0.0103***	0.0237***	0.0042	0.0046	0.1292***	-0.0190***	0.0176***	-0.0282***	0.0300***	0.0151***	-0.0211***	1.0000		
(18)	*Rank_EarnSurp*	0.0013	-0.0122***	0.0112***	0.0677***	0.0129***	0.0168***	0.0423***	0.0479***	0.1291***	0.1091***	-0.0092**	0.0059*	0.0051	0.0077**	-0.0463***	-0.0085**	0.0552***	1.0000	
(19)	*I(Female)*	0.0497***	0.0079**	0.0609***	0.0006	-0.0016	0.0018	-0.0094**	-0.0078**	-0.0180***	0.0595***	-0.0060*	-0.0024	0.0137***	0.0033	0.0214***	0.0377***	-0.0529***	-0.0046	1.0000

Table 4: Determinants of Social Media Content Toxicity

This table presents OLS regression results examining the determinants of content toxicity in social media articles and comments. The dependent variable is toxicity measured separately for articles (*ToxicLang_Art*), comments (*ToxicLang_Com*), and combined content (*ToxicLang*). Independent variables include firm characteristics, market conditions, and CEO attributes. All specifications include industry and year fixed effects. All variables are defined in Appendix A. Standard errors are clustered by author. ***, **, * indicates significance at the 0.01, 0.05, 0.10 level, respectively.

Dep. Variable:	*ToxicLang*								
	All	Articles Only	Comments Only	All	Articles Only	Comments Only	All	Articles Only	Comments Only
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
LogMVE	0.2147***	0.0050	0.2164***	0.2108***	0.0048	0.2126***	0.2134***	0.0050	0.2150***
	(11.06)	(0.58)	(13.20)	(10.96)	(0.56)	(13.12)	(11.16)	(0.59)	(13.29)
ROA	5.0600***	0.8084**	4.3248***	5.1684***	0.8162**	4.4253***	4.8630***	0.7817**	4.1566***
	(4.82)	(2.28)	(4.72)	(4.96)	(2.30)	(4.87)	(4.67)	(2.20)	(4.58)
MTB	0.0185***	0.0004	0.0173***	0.0186***	0.0005	0.0174***	0.0182***	0.0004	0.0171***
	(4.74)	(0.37)	(4.87)	(4.76)	(0.38)	(4.90)	(4.70)	(0.34)	(4.83)
StdRet	31.4362***	4.1020***	27.1210***	29.7343***	3.9981***	25.5259***	31.7689***	4.1588***	27.3835***
	(11.34)	(3.59)	(11.31)	(10.86)	(3.50)	(10.77)	(11.67)	(3.65)	(11.68)
Ind_filing	0.0141	-0.0319	0.0314	0.0156	-0.0318	0.0328	0.0140	-0.0324	0.0319
	(0.21)	(-0.88)	(0.89)	(0.24)	(-0.88)	(0.95)	(0.22)	(-0.91)	(0.93)
Ind_8ks	0.2276***	0.0826*	0.1526***	0.2329***	0.0829*	0.1575***	0.2387***	0.0854*	0.1607***
	(2.87)	(1.80)	(2.85)	(2.95)	(1.81)	(2.93)	(3.06)	(1.87)	(3.05)
Number_prs	-0.0007***	0.0001	-0.0008***	-0.0008***	0.0001	-0.0008***	-0.0007***	0.0001	-0.0007***
	(-4.95)	(1.09)	(-6.21)	(-5.13)	(1.06)	(-6.42)	(-4.49)	(1.32)	(-5.93)
Rank_EarnSurp	-0.0100*	0.0033	-0.0135***	-0.0083	0.0034	-0.0118**	-0.0104*	0.0034	-0.0140***
	(-1.76)	(1.34)	(-2.80)	(-1.46)	(1.38)	(-2.49)	(-1.83)	(1.39)	(-2.93)
I(Female)	0.7236***	-0.0052	0.6989***	0.7185***	-0.0054	0.6940***	0.7309***	-0.0023	0.7030***
	(4.91)	(-0.14)	(5.29)	(4.91)	(-0.15)	(5.29)	(5.00)	(-0.06)	(5.36)
Log_Tenure	-0.0322**	-0.0096	-0.0253*	-0.0308**	-0.0095	-0.0240*	-0.0376**	-0.0110*	-0.0293**
	(-2.07)	(-1.52)	(-1.85)	(-2.00)	(-1.51)	(-1.78)	(-2.42)	(-1.74)	(-2.14)
Length_Art	2.7058***	2.5079***	0.0953*	2.7100***	2.5085***	0.0988*	2.7003***	2.5077***	0.0901
	(24.95)	(34.69)	(1.66)	(25.03)	(34.69)	(1.73)	(25.20)	(34.85)	(1.59)
Length_Com	0.5754***	0.0342***	0.5391***	0.5898***	0.0346***	0.5531***	0.5945***	0.0353***	0.5571***
	(20.34)	(4.86)	(20.69)	(20.91)	(4.93)	(21.30)	(20.95)	(5.00)	(21.39)
Tone_LM_Art	-28.6988***	-9.3375***	-18.6079***	-26.1762***	-9.1632***	-16.2653***			
	(-14.19)	(-8.73)	(-12.63)	(-13.45)	(-8.56)	(-11.64)			
Tone_LM_Com	-5.2836***	0.1371	-5.4452***						
	(-11.07)	(0.45)	(-12.82)						
Tone_FinBERT_Com				-1.0253***	-0.0431**	-0.9819***			
				(-20.44)	(-2.09)	(-22.45)			
Tone_BCJ_Art							-19.6219***	-6.9331***	-12.1266***
							(-10.69)	(-7.39)	(-10.01)
Tone_BCJ_Com							-5.2943***	-0.1261	-5.2204***
							(-16.47)	(-0.85)	(-20.41)
N	121,055	121,055	121,055	121,055	121,055	121,055	121,055	121,055	121,055
adj. R^2	0.41	0.35	0.39	0.41	0.35	0.39	0.41	0.35	0.39
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 5: Toxicity and Future User Engagement

This table examines how past toxicity predicts future user participation. The dependent variables are the proportion of non-toxic commenters and the proportion of comments from non-toxic users. Independent variables include lagged measures of article and comment toxicity over the previous 90 days. Control variables include firm characteristics and market conditions. All specifications include industry and year fixed effects. All variables are defined in Appendix A. Standard errors are clustered by author. ***, **, * indicates significance at the 0.01, 0.05, 0.10 level, respectively.

Dep. Variable:	Prop of Non-toxic Commenters	Prop of Comments coming from Non-Tox Commenters	Prop of Non-toxic Commenters	Prop of Comments coming from Non-Tox Commenters
	(1)	(2)	(3)	(4)
ToxicLang_Art [-90,-5]	-0.0108***	-0.0108***	-0.0125***	-0.0122***
	(-13.99)	(-12.48)	(-13.23)	(-12.41)
ToxicLang_Com[-90, -5]	-0.0335***	-0.0394***	-0.0328***	-0.0388***
	(-12.79)	(-9.83)	(-12.01)	(-9.47)
Tone_LM_Art [-90, -5]	1.5474***	1.4400***	1.0470***	1.0259***
	(8.06)	(7.23)	(4.82)	(4.43)
Tone_LM_Com [-90, -5]	-0.0137***	-0.0113***		
	(-3.45)	(-2.66)		
Tone_FinBERT_Com [-90, -5]			0.0373***	0.0308**
			(2.98)	(2.11)
LogMVE	-0.3024***	-0.3239***	-0.3160***	-0.3351***
	(-7.86)	(-7.93)	(-7.94)	(-7.87)
ROA	5.8380***	5.4371***	5.4583***	5.1223**
	(3.10)	(2.62)	(2.87)	(2.45)
MTB	-0.0143***	-0.0119**	-0.0149***	-0.0124**
	(-2.64)	(-2.04)	(-2.77)	(-2.14)
StdRet	-97.8782***	-93.7981***	-96.5892***	-92.7320***
	(-13.82)	(-12.80)	(-13.52)	(-12.53)
Ind_filing	0.2432	0.1791	0.2454	0.1809
	(1.55)	(1.14)	(1.56)	(1.15)
Ind_8ks	1.0454***	1.0397***	1.0525***	1.0456***
	(3.97)	(3.94)	(4.00)	(3.97)
Number_prs	0.0011**	0.0012***	0.0010**	0.0011**
	(2.50)	(2.63)	(2.33)	(2.48)
Rank_EarnSurp	-0.0213*	-0.0139	-0.0218*	-0.0143
	(-1.69)	(-1.10)	(-1.73)	(-1.13)
I(Female)	-0.2180	-0.1690	-0.2094	-0.1619
	(-1.37)	(-1.00)	(-1.35)	(-0.99)
Log_Tenure	0.0395	0.0489	0.0457	0.0540*
	(1.34)	(1.61)	(1.56)	(1.79)
Sentences_90days	0.0000***	0.0000***	0.0000***	0.0000***
	(8.07)	(6.29)	(8.63)	(6.91)
Comments_90days	0.0036***	0.0043***	0.0034***	0.0042***
	(11.43)	(9.24)	(10.57)	(8.75)
N	121,055	121,055	121,055	121,055
adj. R^2	0.11	0.12	0.11	0.12
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Table 6: Toxicity and Retail Trading Activity

This table examines how toxicity and tone in articles and comments related to retail trading behavior. The dependent variables are the total trading volume by retail investors in the [0,2] day window around article publication (*RetailVolume*) in Columns (1) and (3), and the percentage of total shares traded by retail investors in the same window (*RetailPercent*) in Columns (2) and (4). The data is available for a period of 2010 – 2020. Control variables include firm characteristics and market conditions. All variables are defined in Appendix A. Standard errors are clustered by author. ***, **, * indicates significance at the 0.01, 0.05, 0.10 level, respectively.

Dep. Variable:	*RetailVolume* (1)	*RetailPercent* (2)	*RetailVolume* (3)	*RetailPercent* (4)
ToxicLang_Art	-0.004	0.000	-0.004	0.000
	(-1.46)	(0.08)	(-1.48)	(0.08)
ToxicLang_Com	0.060***	0.001***	0.059***	0.001***
	(16.79)	(15.80)	(16.68)	(15.61)
Tone_LM_Art	-3.132***	-0.022**	-3.181***	-0.020**
	(-4.96)	(-2.21)	(-5.08)	(-1.96)
Tone_LM_Com	-1.917***	-0.009**		
	(-7.35)	(-2.52)		
Tone_FinBERT_Com			-0.093***	-0.001***
			(-7.48)	(-6.39)
LogMVE	0.716***	0.003***	0.716***	0.003***
	(71.54)	(28.48)	(71.50)	(28.50)
ROA	-5.890***	0.001	-5.892***	0.002
	(-20.07)	(0.30)	(-20.05)	(0.33)
MTB	-0.009***	0.000***	-0.009***	0.000***
	(-5.03)	(4.43)	(-5.05)	(4.45)
StdRet	66.302***	0.725***	66.249***	0.723***
	(51.21)	(51.18)	(51.05)	(51.07)
Ind_filing	0.479***	0.004***	0.479***	0.004***
	(26.51)	(9.69)	(26.47)	(9.69)
Ind_8ks	0.060	0.002***	0.059	0.002***
	(1.34)	(2.72)	(1.32)	(2.72)
Number_prs	-0.000	0.000***	-0.000	0.000***
	(-1.27)	(7.77)	(-1.26)	(7.73)
Rank_EarnSurp	0.004**	0.000***	0.005**	0.000***
	(2.11)	(4.67)	(2.16)	(4.74)
I(Female)	0.022	-0.001***	0.022	-0.001***
	(0.64)	(-3.79)	(0.65)	(-3.78)
Log_Tenure	-0.051***	0.001***	-0.051***	0.001***
	(-9.63)	(7.46)	(-9.64)	(7.47)
Length_Art	-0.235***	-0.002***	-0.235***	-0.002***
	(-10.53)	(-5.12)	(-10.54)	(-5.10)
Length_Com	0.110***	0.001***	0.112***	0.001***
	(21.24)	(17.52)	(21.58)	(17.88)
N	100,024	100,024	100,024	100,024
adj. R^2	0.72	0.32	0.72	0.32
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Table 7: Informativeness of Retail Trading Around Toxic Content

This table examines how toxicity relates to the informativeness of retail trading. The dependent variables are cumulative abnormal returns over [3,7] and [8,12] day windows following article publication. Independent variables include retail order imbalances interacted with measures of article and comment toxicity and tone. Retail order imbalance data is available for 2010-2020. Control variables include firm and event characteristics. All specifications include industry and year fixed effects. All variables are defined in Appendix A. Standard errors are clustered by author. ***, **, * indicates significance at the 0.01, 0.05, 0.10 level, respectively.

Dep. Variable:	CAR[3,7] (1)	CAR[8,12] (2)	CAR[3,7] (3)	CAR[8,12] (4)
Retail OIB [0,2] X ToxicLang_Art	0.000	-0.000	0.000	-0.000
	(0.13)	(-0.88)	(0.13)	(-0.85)
Retail OIB [0,2] X ToxicLang_Com	-0.001**	-0.001*	-0.001**	-0.001*
	(-2.38)	(-1.75)	(-2.38)	(-1.80)
Retail OIB [0,2]	0.002	0.001	0.002	0.001
	(1.59)	(0.88)	(1.50)	(1.03)
ToxicLang_Art	0.000	0.000	0.000	0.000
	(0.92)	(1.52)	(0.92)	(1.52)
ToxicLang_Com	-0.000	-0.000	-0.000	0.000
	(-0.30)	(-0.07)	(-0.28)	(0.05)
Tone_LM_Art	-0.004	-0.010	-0.004	-0.011
	(-0.30)	(-0.83)	(-0.30)	(-0.94)
Tone_LM_Com	0.002	0.001		
	(0.22)	(0.07)		
Tone_FinBERT_Com			0.000	0.000
			(0.27)	(1.09)
Retail OIB [0,2] X Tone_LM_Art	-0.229***	-0.077	-0.232***	-0.065
	(-2.64)	(-0.86)	(-2.68)	(-0.73)
Retail OIB [0,2] X Tone_LM_Com	0.002	0.033		
	(0.03)	(0.54)		
Retail OIB [0,2] X Tone_FinBERT_Com			0.001	-0.002
			(0.30)	(-0.69)
LogMVE	-0.000***	0.000	-0.000***	0.000
	(-2.77)	(1.14)	(-2.76)	(1.15)
ROA	0.022***	0.004	0.022***	0.004
	(3.44)	(0.70)	(3.44)	(0.69)
MTB	-0.000	0.000	-0.000	0.000
	(-0.10)	(1.49)	(-0.10)	(1.48)
StdRet	-0.006	0.085***	-0.006	0.086***
	(-0.25)	(3.50)	(-0.24)	(3.53)
Ind_filing	0.000	0.001**	0.000	0.001**
	(0.76)	(1.98)	(0.76)	(1.97)
Ind_8ks	-0.000	0.001	-0.000	0.001
	(-0.48)	(0.60)	(-0.48)	(0.59)
Number_prs	-0.000***	-0.000**	-0.000***	-0.000**
	(-6.01)	(-2.15)	(-6.01)	(-2.14)
Rank_EarnSurp	0.000***	0.000***	0.000***	0.000***
	(4.52)	(6.11)	(4.52)	(6.10)
I(Female)	0.000	0.001	0.000	0.001
	(0.63)	(1.39)	(0.63)	(1.38)
Log_Tenure	0.000***	0.000***	0.000***	0.000***
	(3.83)	(2.81)	(3.83)	(2.80)
Length_Art	-0.000	-0.000	-0.000	-0.000
	(-0.58)	(-1.40)	(-0.57)	(-1.42)
Length_Com	-0.000	-0.000*	-0.000	-0.000**
	(-0.05)	(-1.87)	(-0.08)	(-2.00)
N	100,024	100,024	100,024	100,024
adj. R^2	0.004	0.004	0.004	0.004
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Table 8: Market Response to Toxic Social Media Content

This table examines the market reaction to toxicity. The dependent variable is the three-day cumulative abnormal return [-1,+1] around article publication. Independent variables include separate measures of article and comment toxicity and tone. Control variables include firm and event characteristics. All specifications include industry and year fixed effects. All variables are defined in Appendix A. Standard errors are clustered by author. ***, **, * indicates significance at the 0.01, 0.05, 0.10 level, respectively.

Dep. Variable:	CAR[-1,+1]	
	(1)	(2)
ToxicLang_Art	0.008	0.009
	(1.52)	(1.54)
ToxicLang_Com	-0.024***	-0.019***
	(-4.20)	(-3.40)
Tone_LM_Art	18.753***	17.984***
	(10.62)	(10.16)
Tone_LM_Com	2.830***	
	(5.54)	
Tone_FinBERT_Com		0.406***
		(10.25)
LogMVE	0.008	0.009
	(0.68)	(0.72)
ROA	2.324***	2.268***
	(3.57)	(3.48)
MTB	-0.004*	-0.004*
	(-1.83)	(-1.89)
StdRet	1.986	2.467
	(0.73)	(0.91)
Ind_filing	-0.069**	-0.069**
	(-2.04)	(-2.06)
Ind_8ks	-0.047	-0.050
	(-0.35)	(-0.37)
Number_prs	-0.001***	-0.001***
	(-4.88)	(-4.81)
Rank_EarnSurp	0.029***	0.028***
	(5.88)	(5.76)
I(Female)	-0.051	-0.052
	(-0.87)	(-0.89)
Log_Tenure	0.054***	0.053***
	(4.61)	(4.57)
Length_Art	-0.024	-0.025
	(-0.71)	(-0.75)
Length_Com	-0.011	-0.020***
	(-1.61)	(-2.85)
N	121,055	121,055
adj. R^2	0.01	0.01
Controls	Yes	Yes
Industry FE	Yes	Yes
Year FE	Yes	Yes

Table 9: Toxic Social Media Content and Price Discovery

This table examines the relation between social media content characteristics and the speed of price discovery around earnings announcements. The dependent variable is the intraperiod price efficiency metric (IPE) calculated over various windows. Independent variables include measures of article and comment toxicity and tone. Control variables include firm and event characteristics. All specifications include industry and year fixed effects. All variables are defined in Appendix A. Standard errors are clustered by author. ***, **, * indicates significance at the 0.01, 0.05, 0.10 level, respectively.

Dep. Variable:	IPE [-1,+2] (1)	IPE [-3,+3] (2)	IPE [-1,+2] (3)	IPE [-3,+3] (4)
Agg_ToxicLang_Art	-0.004***	-0.001	-0.004***	-0.000
	(-2.63)	(-0.49)	(-2.22)	(-0.19)
Agg_ToxicLang_Com	-0.003***	-0.005***	-0.003***	-0.005***
	(-2.90)	(-3.00)	(-2.98)	(-3.00)
Agg_Tone_LM_Art	1.003	2.050	1.417	2.461*
	(1.08)	(1.40)	(1.56)	(1.71)
Agg_Tone_LM_Com	0.605	0.650		
	(0.91)	(0.72)		
Agg_Tone_FinBERT_Com			-0.040***	-0.038*
			(-2.72)	(-1.96)
LogMVE	0.048***	0.064***	0.049***	0.066***
	(6.79)	(5.47)	(6.90)	(5.53)
ROA	0.628*	0.526	0.618*	0.517
	(1.93)	(0.90)	(1.90)	(0.89)
MTB	-0.002**	-0.003	-0.002*	-0.002
	(-1.97)	(-1.44)	(-1.93)	(-1.41)
StdRet	-3.537***	-6.371***	-3.539***	-6.384***
	(-3.12)	(-3.57)	(-3.12)	(-3.58)
Ind_8ks	0.025	0.084	0.026	0.085
	(0.67)	(1.56)	(0.70)	(1.59)
Number_prs	-0.000	0.000	-0.000	0.000
	(-0.41)	(0.23)	(-0.36)	(0.29)
Rank_EarnSurp	-0.005	-0.007	-0.004	-0.006
	(-1.50)	(-1.25)	(-1.39)	(-1.18)
I(Female)	0.023	-0.088	0.026	-0.087
	(0.59)	(-1.60)	(0.65)	(-1.58)
Log_Tenure	-0.013*	-0.016	-0.013*	-0.015
	(-1.93)	(-1.57)	(-1.89)	(-1.55)
Agg_Length_Art	-0.010	-0.012	-0.009	-0.012
	(-0.61)	(-0.46)	(-0.59)	(-0.46)
Agg_Length_Com	0.005	0.005	0.005	0.005
	(1.36)	(0.94)	(1.42)	(1.00)
No_Article_Ind	0.049***	0.050*	0.044***	0.045
	(2.32)	(1.67)	(2.08)	(1.51)
N	11,326	11,527	11,326	11,527
adj. R^2	0.05	0.02	0.06	0.02
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Table 10: CEO Turnover and Changes in Social Media Toxicity

This table analyzes changes in social media content toxicity around CEO transitions during 2010-2020. The analysis compares male-to-female transitions with male-to-male transitions in a [-3,+3] month window around the transition. The specification includes firm and year fixed effects and employs entropy balancing to account for differences in firm characteristics. All variables are defined in Appendix A. Standard errors are clustered by author. ***, **, * indicates significance at the 0.01, 0.05, 0.10 level, respectively.

Dep. Variable:	ToxicLang (1)	ToxicLang_Art (2)	ToxicLang_Com (3)	ToxicLang (4)	ToxicLang_Art (5)	ToxicLang_Com (6)
Male to Female X Post	1.028**	0.386	0.579*	1.006**	0.386	0.562*
	(2.47)	(1.56)	(1.74)	(2.44)	(1.58)	(1.71)
Post	0.208	0.267	0.062	0.208	0.284	0.044
	(0.49)	(0.79)	(0.27)	(0.49)	(0.85)	(0.19)
Tone_LM_Art	-17.216*	-1.969	-14.718**	-16.772*	-2.662	-13.605**
	(-1.91)	(-0.35)	(-2.25)	(-1.89)	(-0.49)	(-2.07)
Tone_LM_Com	-2.809	-0.889	-1.310			
	(-1.00)	(-0.33)	(-0.86)			
Tone_FinBERT_Com				-0.472	0.216	-0.617***
				(-1.53)	(0.87)	(-3.12)
LogMVE	0.477	0.765***	-0.066	0.456	0.766***	-0.084
	(0.92)	(2.63)	(-0.14)	(0.88)	(2.65)	(-0.17)
ROA	14.202	-3.772	12.178**	13.945	-3.589	11.771**
	(1.62)	(-0.63)	(2.57)	(1.59)	(-0.60)	(2.48)
MTB	-0.056**	-0.028	-0.023	-0.054**	-0.029	-0.020
	(-2.38)	(-1.43)	(-1.34)	(-2.31)	(-1.49)	(-1.25)
StdRet	-11.074	-8.139	-3.810	-11.139	-7.952	-4.067
	(-0.52)	(-0.70)	(-0.23)	(-0.53)	(-0.69)	(-0.25)
Ind_filing	0.054	-0.022	0.095	0.060	-0.024	0.102
	(0.17)	(-0.11)	(0.50)	(0.19)	(-0.13)	(0.53)
Ind_8ks	-1.178*	-0.746	-0.439	-1.144*	-0.750	-0.408
	(-1.86)	(-1.60)	(-1.24)	(-1.79)	(-1.61)	(-1.17)
Number_prs	0.025***	0.016***	0.008***	0.025***	0.016***	0.008***
	(3.56)	(2.61)	(3.06)	(3.57)	(2.70)	(2.98)
Log_Tenure	0.125	0.089	0.052	0.124	0.094	0.046
	(1.12)	(1.01)	(0.83)	(1.11)	(1.08)	(0.73)
Rank_EarnSurp	0.016	0.020	0.015	0.016	0.019	0.016
	(0.35)	(0.71)	(0.38)	(0.35)	(0.68)	(0.40)
Length_Art	0.450***	-0.051	0.494***	0.455***	-0.051	0.499***
	(5.24)	(-0.96)	(7.71)	(5.34)	(-0.97)	(7.65)
Length_Com	2.976***	2.875***	-0.017	2.981***	2.873***	-0.011
	(10.41)	(15.26)	(-0.12)	(10.38)	(15.17)	(-0.08)
N	5,511	5,511	5,511	5,511	5,511	5,511
adj. R^2	0.46	0.39	0.54	0.46	0.39	0.54
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 11: GPT-based Alternative Measure of Sentiment

This table presents robustness tests using an alternative measure of comment sentiment. The dependent variables are: (1) total retail trade volume [0,2] days, (2)) retail trade percentage [0,2] days, (3) cumulative abnormal returns [3,7] days, (4) three-day cumulative abnormal returns [-1,+1] around article publication, and (5) intraperiod price discovery (IPE) [-1,+2] days around earnings announcements. All models include industry and year fixed effects, with variables defined in Appendix A. Standard errors are clustered by author. ***, **, * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively.

	Retail Trading			Returns	Price Discovery
Dep. Variable	Volume	Percentage	CAR[3,7]	CAR[-1,+1]	IPT[-1,+2]
	(1)	(2)	(3)	(4)	(5)
ToxicLang_Art	-0.004	0.000	0.000	0.008	-0.004***
	(-1.48)	(0.07)	(0.92)	(1.52)	(-2.70)
ToxicLang_Com	0.060***	0.001***	-0.000	-0.019***	-0.003***
	(16.81)	(15.82)	(-0.17)	(-3.37)	(-2.96)
ROI [0,2]			0.002		
			(1.57)		
ROI [0,2] X ToxicLang_Art			0.000		
			(0.15)		
ROI [0,2] X ToxicLang_Com			-0.001**		
			(-2.42)		
Tone_LM_Art	-3.262***	-0.024**	-0.006	17.393***	1.219
	(-5.23)	(-2.33)	(-0.49)	(9.98)	(1.30)
ROI [0,2] X Tone_LM_Art			-0.227***		
			(-2.61)		
Tone_GPT_Com	-0.064***	-0.000	0.001**	0.545***	-0.007
	(-5.78)	(-0.68)	(2.04)	(14.48)	(-0.63)
ROI [0,2] X Tone_GPT_Com			-0.001		
			(-0.30)		
N	100,024	100,024	100,024	121,055	11,326
adj. R2	0.72	0.32	0.004	0.01	0.05
Controls	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes